

**DESIGN-FOR-MANUFACTURABILITY (DFM)  
FOR SYSTEM-IN-PACKAGE (SIP) APPLICATIONS**

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by

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**DESIGN-FOR-MANUFACTURABILITY (DFM)**  
**FOR SYSTEM-IN-PACKAGE (SIP) APPLICATIONS**

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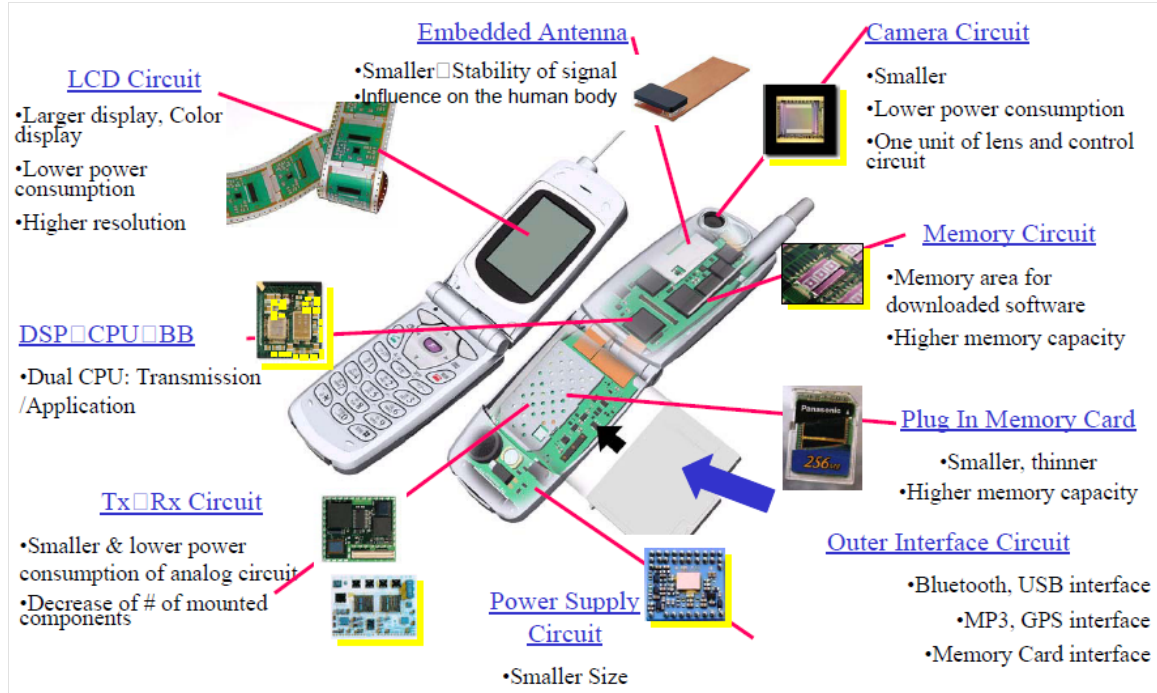
# CHAPTER I

## INTRODUCTION

Fueled in large part by the growing convergence of communications, computing and consumer electronics, the use of System-in-Package (SiP) [15] as design methodology provides distinct performance, cost and size advantages. The portable/wireless revolution is driving towards small, lightweight, high-performance, reliable systems, all at costs far below than those associated with historic electronic products and markets. This is possible only if high volume manufacturability is ensured, ideally 100%.

Microelectronic systems packaging involves microscale and nanoscale layout dimensions. Moreover, SiP designers must deal simultaneously with multiple design constraints while also meeting several performance specifications across multiple frequency bands. The ever increasing operating frequencies and the drive to implement mixed signal systems in cost effective technologies have significantly reduced the process tolerance margins. During manufacturing, process variations will cause design parameters to deviate from their nominal values.

As speed of the signal increases, high-frequency effects take over, and even the shortest lines can suffer from problems such as ringing, crosstalk, reflections and ground bounce, seriously hampering the response of the signal, thus damaging signal integrity and power integrity (SI/PI). As a result, the manufactured electronic packaging structure may no longer meet performance specifications that it was designed to satisfy. Hence, statistical variations of the performance should be considered for achieving a design point and a feasible yield level. Cost effective digital and RF system integration is possible only after attaining sufficient manufacturing yield during production. Figure 1 shows how various components using System-in-Package (SiP)

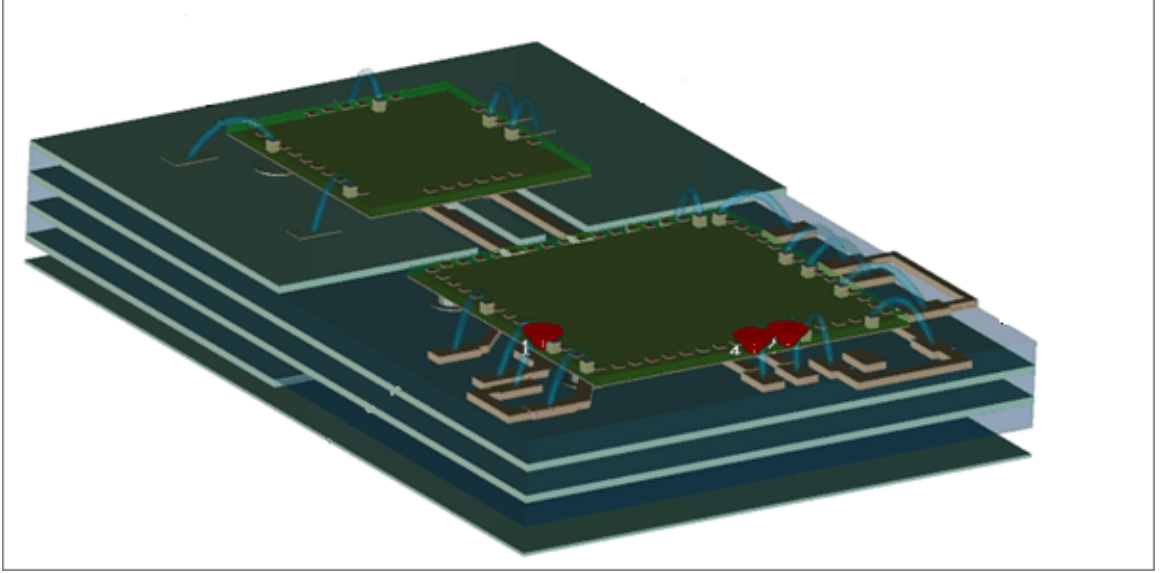


**Figure 1:** System-in-Package (SiP) technology in a cellular phone.

technology are integrated in a cellular phone.

A designer's primary objective is to design a functioning product within given economic and schedule constraints. However, research has shown that decisions made during the design period determine 70% of the product's costs while decisions made during production only account for 20% of the product's costs. Further, decisions made in the first 5% of product design could determine the vast majority of the product's cost, quality and manufacturability characteristics. This indicates the great leverage that Design-for-Manufacturability (DFM) can have on a company's success and profitability.

This dissertation addresses the statistical analysis and layout parameters optimization for highspeed digital systems and embedded RF passive circuits. In aggressive designs with cost-effective manufacturing techniques, narrowing tolerance margins no longer satisfy the worst-case design and operation scenarios. Furthermore, Monte Carlo simulations are infeasible for computing yield because of simulation complexities



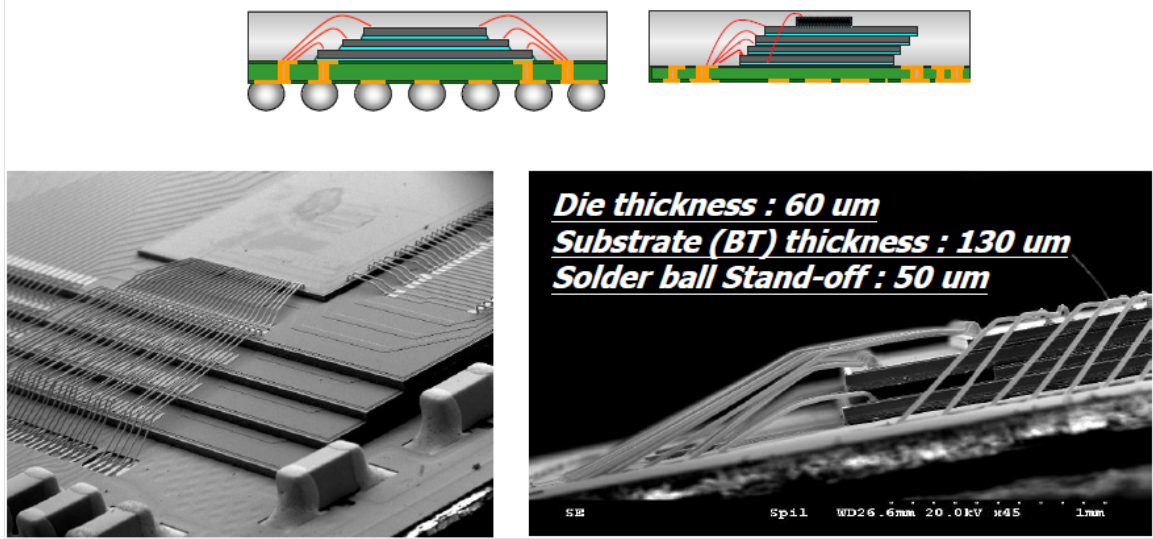
**Figure 2:** 3-D cross-sectional view of a System-in-Package (SiP).

of large digital systems and embedded RF components. This dissertation introduces an alternative to Monte Carlo statistical analysis method, and classical worst-case verification approach for large digital systems with embedded RF components.

### ***1.1 System-in-Package (SiP)***

Technology advances and market drivers have produced a renaissance in multichip packaging solutions. System-in-Package (SiP) solutions are increasingly found in a broad range of market segments, including consumer electronics such as digital cameras and camcorders, automotive, military/aerospace, medical, computer, and telecommunications products. Semiconductor industry demands for higher levels of integration, lower costs, and a growing awareness of complete system configuration have continued to drive SiP solutions. [7]

The system-in-package concept seeks to integrate multiple ICs (each optimally suited for its function by design as well as wafer process) along with other system components like passives, interconnects and antenna into a single functional package. SiP thus exploits the best features of existing chip technologies and at the same time



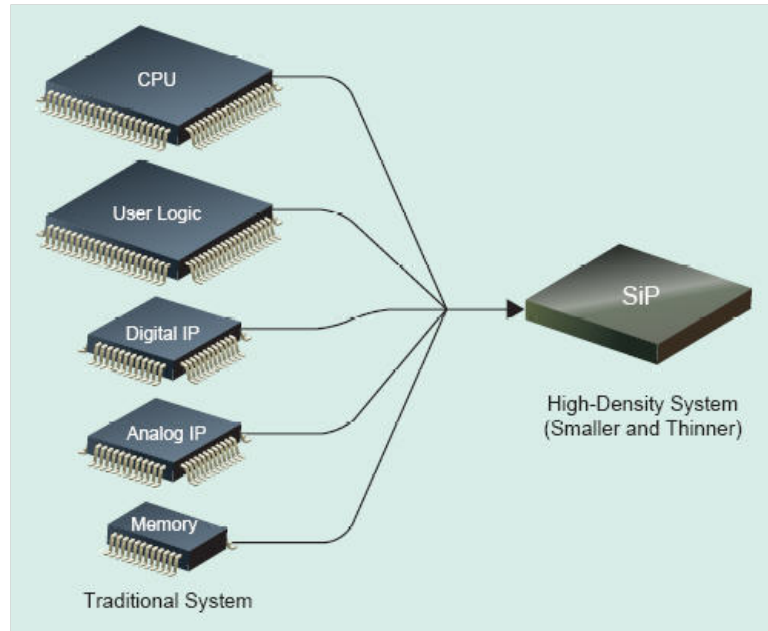
**Figure 3:** SiP using Wirebond technology.

achieves a low cost and highly integrated system. A SiP generally consists of multiple chips stacked and connected within a package. Therefore, it allows to reduce the printed circuit board (PCB) area and to improve the system performance and power consumption (by reducing the parasitic R, L, C size on the PCB).

In its most simple definition, a System-in-Package (SiP) consists of active devices (one or multiple ICs), passive components and discrete devices designed and assembled into a standard or custom package to achieve a modular function previously accomplished by using several separated single chip packages. The SiP forms a functional block or module that can be used for board level manufacturing.

Usually, SiP development time is shorter since the components do not require as much design verification at the functional level. Thus, the cost to develop the SiP design can be substantially lower than it is for an System on Chip (SoC). Furthermore, if a complicated substrate is limited only to the SiP module, then the entire system board does not require as many layers or impedance control. That reduces the system PCB costs and allows changes to be focused on the SiP itself, rather than on the entire system board.





**Figure 4:** Integration of various components to form a System-in-Package (SiP).

Chip/component configuration	Technology
Side-by-side placement	<p>Substrate: organic laminate, ceramic, glass, silicon, lead frame</p> <p>Chip interconnections: wire bond and/or flip chip</p> <p>Plus passive components → integrated into the substrate</p> <p>discrete (chip-scale package, surface-mount device)</p>
Stacked structure	<p>Package-on-package</p> <p>Package-in-package</p> <p>Stacked die → wire bond, wire bond plus flip chip</p> <p>Chip-to-chip/wafer → flip chip, face to face through silicon wafer-level 3-D stack wafer to wafer</p>
Embedded structure	<p>Chip in pcb/polymer → single layer multilayer 3-D stack</p> <p>Wafer-level thin-chip integration → single layer stacked functional layers</p>

**Figure 5:** SiP technology includes single-and multichip modules (top), stacked dice (middle), and 3-D packaging (bottom).

SiPs are usually segmented into three technology types: modules (single- or multichip), stacked dice and 3-D packaging. Figure 5 shows the different types of SiPs.

### **1.1.1 Design Challenges for System-in-Package (SiP)**

A key advantage of the SiP is its flexibility of integration, allowing designers a choice of memory densities or memory technologies, such as flash or SRAM. Similarly, highly complex or highly specialized chips that provide unique functionality or precision become possible with SiP technology. For example, it is possible to combine GaAs high-performance designs with standard CMOS digital chips for use in an RF application.

The package usually adopted by a SiP is based on a Ball Grid Array (BGA). The external contacts consist in a grid of balls placed underneath the lower surface of the package; the lower part of the SiP is composed by a substrate, in which two or more metallization levels can be realized, in order to implement the interconnects distributing the signals to the different chips of the SiP. These interconnects, however, suffer from signal integrity problems due to their high parasitics. In particular, inductive and capacitive crosstalk, as well as simultaneous switching noise (SSN) and intersymbol interference (ISI) have been identified as the most detrimental effects for signal integrity in a SiP.

Therefore, one of the main concerns for SiP technology is the integrity of the communication between the different chips within the package. The continuous decreasing of the power supply and the escalating of the operating frequencies are making these problems increasingly critical. [23]

## **1.2 Design-for-Manufacturability (DFM)**

Signal Integrity (SI) and Power Integrity (PI) gained a lot of attention as data rates soar into multi-gigahertz territory. Signal integrity issues in electronics packaging can have many drastic consequences for digital designs. Yield may be lowered, sometimes

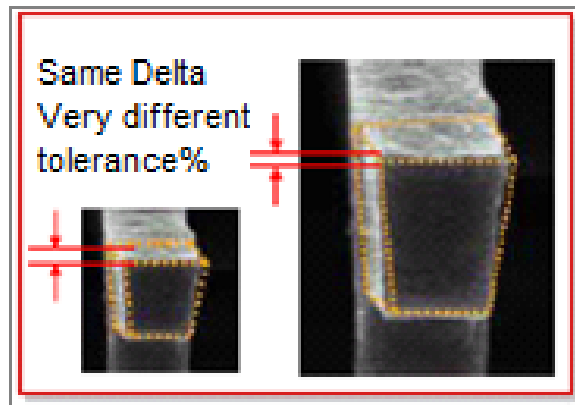
drastically. This is where Design-for-Manufacturability (DFM) fits in.

Design for manufacturability is a design methodology intended to ease the manufacturing process of a given product. In the PCB design process DFM leads to a set design guidelines that attempt to ensure manufacturability. By doing so, probable production problems may be addressed during the design stage.

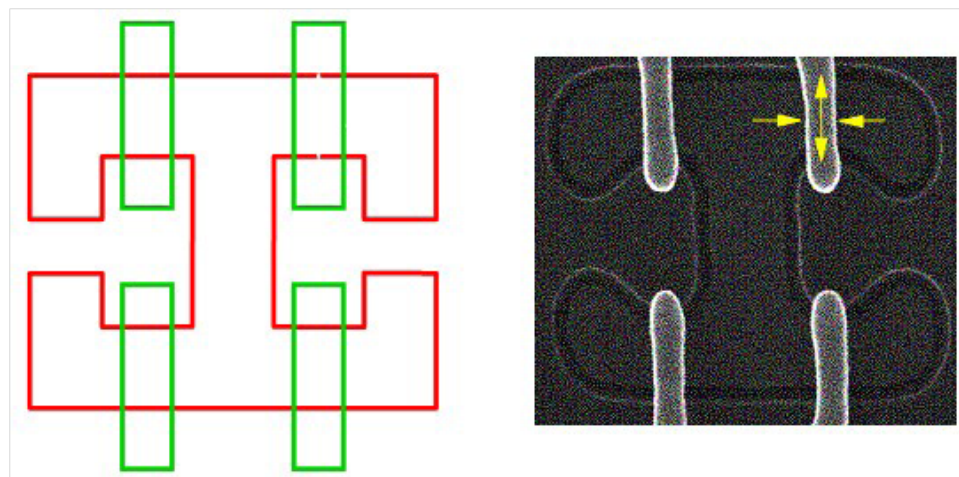
Ideally, DFM guidelines take into account the processes and capabilities of the manufacturing industry. Therefore, DFM is constantly evolving. As manufacturing companies evolve and automate more and more stages of the processes, these processes tend to become cheaper. DFM is usually used to reduce these costs.

### **1.2.1 Need for DFM**

The layout dimensions of the high-speed digital and RF layouts are fast approaching the sub-micron level to match the ever shrinking feature size of the Integrated Chip (IC). Since the technology used to manufacture the SiP's cannot be replaced year-after-year by the profit driven industries, the process variations during manufacturing still remains the same. Hence, the tolerance percentage values are increasing [26]. Therefore, the SiP's performance measures and output yield are becoming more and more sensitive to the process fluctuations. To mitigate this problem, the performance specifications and the output yield have to be studied during the design phase itself. However, to consider all the variations of the various design parameters and create the experiments to perform EM simulations is time and money consuming. In the present scenario where the successful industries are differentiated from the others based on their time to market parameter, EM simulations of thousands of cases is a bad choice. DFM is the best possible solution available. [1] [20]



**Figure 6:** Change in tolerance percentage with miniaturization.



**Figure 7:** Need for Design-for-Manufacturability.

## 1.2.2 DFM statistical approaches

### 1.2.2.1 *Worst Case method*

In an electrical system, the classical approach to account for process and operational uncertainties is the worst-case analysis. [22] After the worst-case combination of the design parameters is verified, all products are expected to meet the specifications. This conservative design approach has major limitations. First, it requires an initial guess of the worst-case scenario. Estimation of design parameter effects on performance may not be obvious. For large number of parameters, full factorial simulations to find the worst-case point is inefficient. Furthermore, with a large number of performance measures, it becomes very difficult to find the worst-case parameter combination for each performance measure. Second, the worst-case combination, where all design parameters are at their extremes, has very low probability of occurrence. Therefore, designs based on the worst-case analysis may underestimate the performance and increase the design effort. Third, the worst-case verification provides very limited quantitative information about the design, which can be used for further improvement in performance. It is also important to note that the worst-case has very low probability of occurrence.

Instead of worst-case, statistical analysis methods can be employed to address the challenges in next generation systems. Statistical analysis does not require prior knowledge or assumption of the worst-case combination. Instead of a worst-case number it provides a probability distribution, which is useful for parametric yield estimations and design refinements. Monte Carlo, summarized in the next section, is a popular method for generating performance probability distributions and yield figures.

### 1.2.2.2 Monte Carlo method

Parametric yield is defined as the percentage of the circuits or systems satisfying performance specifications in the presence of statistical perturbations. The most straightforward and common method to estimate parametric yield is Monte Carlo analysis [11]. This technique depends on simulating a large number of design parameter combinations for generating the performance statistics. The values of the design parameters are generated from random variables with associated probability distributions and correlations. Then, the yield is approximated as the ratio of the number of acceptable instances to the total number of Monte Carlo runs. This can be formalized as:

$$Y = \int_{-\infty}^{\infty} z(x)f(x)dx \quad (1)$$

where  $z(x)=1$  if all design values (x) satisfy the specifications, and  $z(x)=0$  otherwise. In Equation 1,  $f(x)$  is the joint probability density function of design parameters. Then the yield can be estimated as:

$$\hat{Y} = \frac{1}{N} \sum_{i=1}^N z(x_i) \quad (2)$$

and

$$\hat{Y} = \frac{1}{N} \sum_{i=1}^N z(x_i) \frac{f(x_i)}{h(x_i)} \quad (3)$$

The main drawbacks of Monte Carlo method are the large number of experiments that should be simulated to get an accurate analysis. Electromagnetic (EM) simulations consume a lot of time and money for their execution. So, to get the Monte Carlo experiments done using Em simulator will almost be a never ending process. An alternative approach to Monte Carlo method is Design of Experiments (DOEs) method. The next section will give a brief explanation about the DOEs and its advantages over Monte Carlo method.

### *1.2.2.3 Design of Experiments*

Design of experiments method is a sequence of tests, where input parameters are varied in a planned manner [2]. Using DOE, the circuit performance can be represented as empirical functions of the design parameters [6]. To obtain the empirical functions, a series of planned experiments (simulations) can be performed with different levels of the input design parameters. Then, Monte Carlo instances can be applied to these surrogate functions to generate the performance statistics. In summary, DOE principles have emerged as a powerful alternative to worst case analysis and Monte Carlo Analysis. Hence, the statistical analysis for embedded RF circuits are based on planned DOE arrays without resorting to Monte Carlo type of simulations.

## ***1.3 Completed Research***

Contrary to integrated circuit design, statistical analysis methods have not been widely applied to system-level signal integrity analysis. This has been mainly due to the large voltage and timing margins in low data rate buses, where statistical analysis was not necessary. In other words, the worst-case analysis was sufficient. Besides, accurate electromagnetic modeling and simulation techniques for signal integrity measures of large systems were not commonly available. However, emerging memory and I/O intensive products with higher bandwidths consume all available voltage and timing margins for achieving cost effective, high performance designs. Hence, statistical analysis becomes critical for meeting the specifications of high speed systems. In accordance with the improvements in system-level modeling and simulation techniques, statistical system-level signal integrity analysis methodologies must be developed.

Research in the area of DFM and design centering for SI/PI combined has not been done previously. None of the commercial tools support DFM at the package level. Main reason is due to the modeling complexity which scales with smaller grid size. DFM approaches in ADS, Spectre are based on equivalent circuit models. All these

commercial tools make use of Monte-Carlo simulations to generate statistical distributions. The proposed method supports DFM at the package layout level. Statistical distributions will be generated directly from the layout using convolution techniques instead of traditional Monte-Carlo simulations. The time taken for the generation of statistical distributions is less when compared to Monte-Carlo method.

Some work has been done in the DFM at the layout level in Epsilon group at Georgia Institute of Technology [17] [19]. The work done shows the application of DFM at package layout level. The implementation assumes that the performance measure data obtained from the design of experiments can be interpolated using regression expression and there would not be any regression error while curve-fitting. Hence, when the final yield value is calculated, the regression error propagates since the regression expression coefficients are used in calculation of the parametric yield value. In this dissertation, the regression error is taken into account while calculating the yield value. I propose three terms for the parametric yield, average yield value and boundary yield values, and hence give out a range instead of a single value. The proposed methodology is shown in the next chapter.

## ***1.4 Dissertation Outline***

Chapter 2 discusses modeling and formulation of the statistical analysis for digital systems and embedded RF components. In this chapter, statistical analysis and diagnosis methodology is introduced. Major design of experiment principles are summarized. Selection of the experiment plan for the statistical analysis is discussed.

Chapter 3 demonstrates the methodology using two test cases. The first case is a 4 layer package layout and the second case is a RF bandpass filter. In this chapter, parametric yield for both the test cases is computed. The methods for increasing yield are discussed.

Chapter 4 summarizes the methodology used and the research that has been done.



It also discusses the future work and improvements that can be done based on the present work.

# **CHAPTER II**

## **STATISTICAL ANALYSIS USING DESIGN OF EXPERIMENTS**

The need for Design-for-manufacturing methods in the case of System-in-Package (SiP) applications has been discussed in the previous chapter. Chapter two introduces and explains the basic flow of statistical analysis of SiP.

This dissertation uses design of experiments (DOE) based simulations to efficiently characterize the statistical disturbance space. The process starts by identifying the key performance measures, significant parameters, and the statistical distributions of these parameters. Sensitivity functions of performance measures as functions of the design parameters are obtained through planned simulations. After obtaining the sensitivity functions, regression analysis is used to curve fit the DOE simulation data so that the performance specifications for all possible combinations of design parameters can be achieved without running the EM simulations. When the required regression fitness is obtained, the statistical variations of the design parameters are reflected on the performance for computing the performance variations. Computing the joint probability distribution function (pdf) of the analyzed performance measures, yield and performance analysis can be done at this stage of the analysis. The final step is the design centering of the input parameters to maximize the yield output.

The chapter starts with the flowchart of the proposed methodology, and then discusses the different steps and analyses used to help increase the output yield. The various steps involved in the analyses are:

1. Design of experiments
2. Sensitivity analysis

3. Regression analysis
4. Convolution and probability density functions (*pdf's*)
5. Yield estimation/optimization
6. Design centering

## ***2.1 Statistical Analysis Flowchart***

Figure 8 shows the flowchart of the proposed methodology [19]. Selecting the correct design parameters and performance specifications forms the first step in this methodology. Significant design parameters are selected based on sensitivity analysis through circuit/electromagnetic (EM) simulations of the layout. Mixed Signal Design Tools (MSDT)- 1 [3] [4] [5] is used for the simulation of the examples in this thesis. MSDT-1 implements the multi-layer finite difference method for simulating the multi-layer packages in the presence of apertures and transmission lines. Each performance measure is best approximated by the linear and piece-wise linear terms by forming a regression equation.

The probability density function (PDF) of the performance specifications are obtained using the convolution of the design parameter distributions. The joint probability density function (JPDF) is obtained by combining the PDF's of all the performance specifications. The design yield is computed as an integral of the joint probability density of distribution data bounded by the performance specifications. Design centering of the input parameters is done using the experiments that satisfy the performance specifications

An example is used to explain each step in the proposed methodology. The next section introduces the setup of the example.

## ***2.2 Test Case***

A 7-layer package with apertures and holes is used to explain the proposed methodology. Figure 9 shows the package with 7 layers.

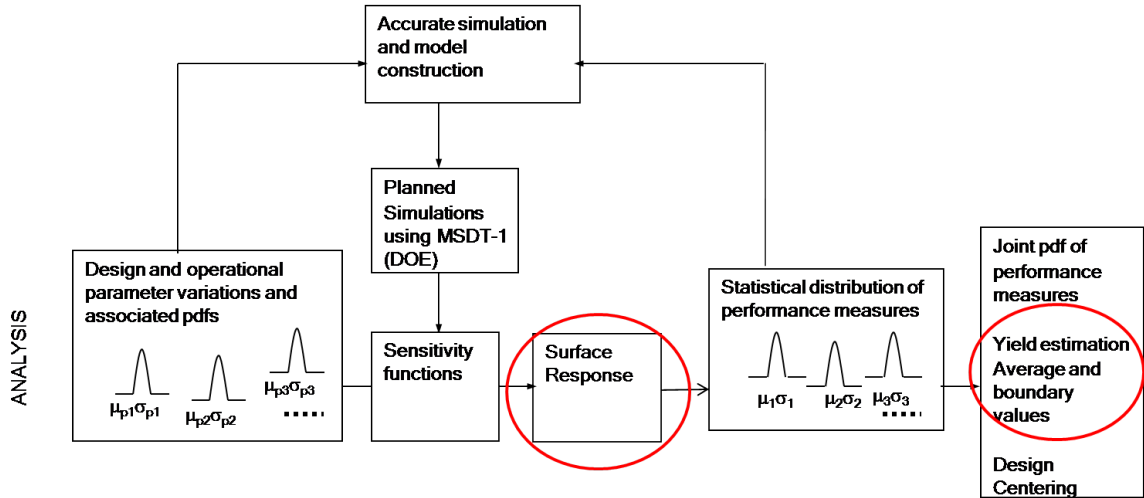
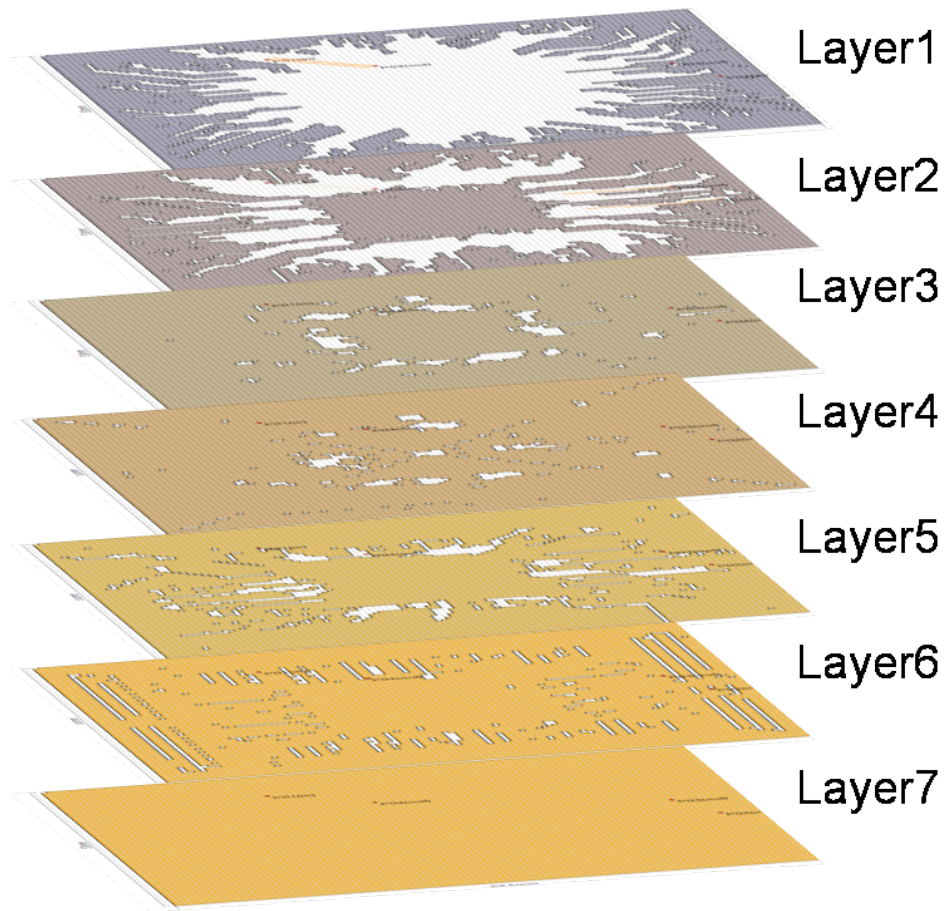


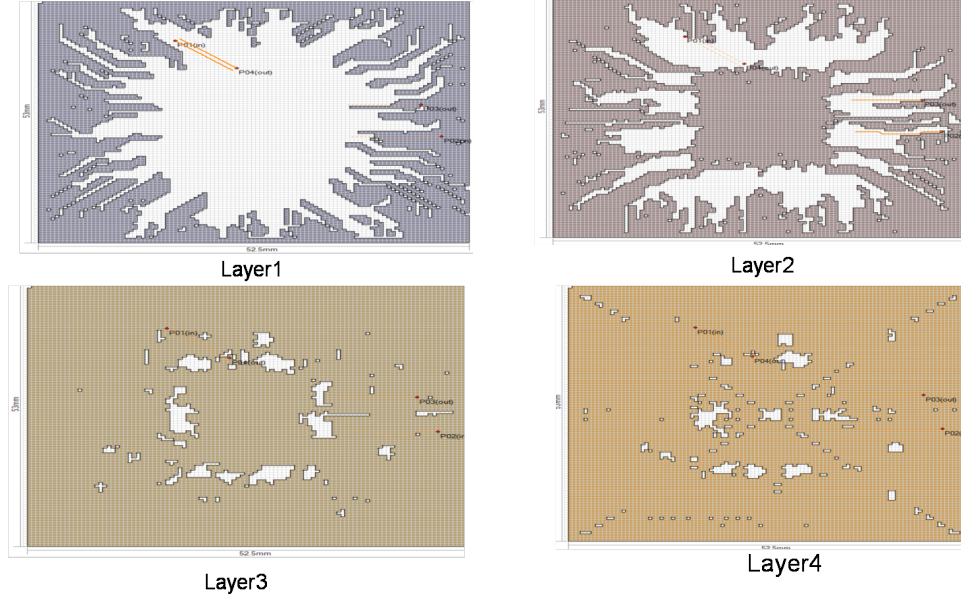
Figure 8: System level statistical analysis method [19].



## 7 layer Package Layout

Figure 9: 7-layer package.

Two transmission lines are present on Layer1 (ports 1 and 4 are connected) and two more are present on Layer2 (ports 2 and 3 are connected). Ports are connected at the ends of transmission lines. The simulation data is obtained from MSDT 1 [3] [4] [5]. Figures 10 and 11 show the planes, transmission lines and the port locations.

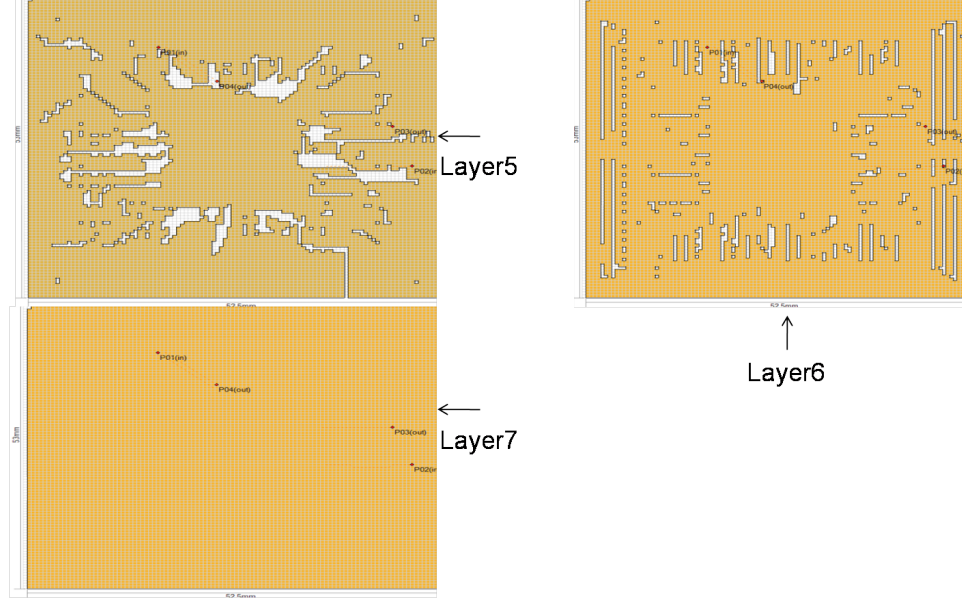


**Figure 10:** Top 4 layers with transmission lines and port locations.

### 2.3 *Selection of design parameters and performance measures*

Selection of performance measures is relatively an easy task since the designer knows what the end consumer really looks at to validate the product. Since there will be a lot of input parameters a designer might be interested, it is very important that he knows which parameters will affect the performance measures the most. If the number of design parameters is less than 10, then the designer can use all the parameters in his analysis. If the number of parameters is more than 10, then the designer can use sensitivity plots to select which parameters affect the performance measures the most and then use those parameters to calculate the yield value and optimize the yield.

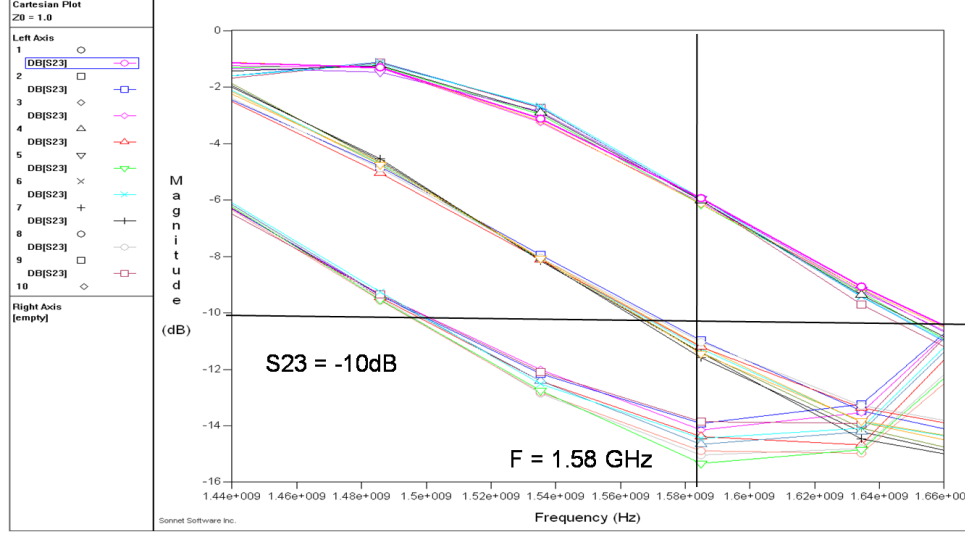
The design parameters considered for the test case are



**Figure 11:** Bottom 3 layers.

1. Dielectric thickness between layers 1 and 2 diel 1
2. Dielectric thickness between layers 2 and 3 diel 2
3. Dielectric thickness between layers 3 and 4 diel 3
4. Dielectric thickness between layers 4 and 5 diel 4
5. Dielectric thickness between layers 5 and 6 diel 5
6. Line Width of the transmission lines - Linewidth
7. Permittivity between layers 1 and 2 Er1
8. Permittivity between layers 2 and 3 Er2
9. Permittivity between layers 3 and 4 Er3
10. Permittivity between layers 4 and 5 Er4

The performance specification that is seen is the insertion loss between ports 2 and 3 at an operating frequency of 1.58GHz. The value of the insertion loss should be less than  $-10$  dB. Figure 12 shows the response for all the design of experiments.



**Figure 12:** Insertion loss between ports 2 and 3 for the design of experiments.

## 2.4 Design of Experiments

Experiments are performed in virtually all fields of enquiry, usually to discover something about a particular process or system. Literally, an experiment is a test. A designed experiment is a test or series of tests in which purposeful changes are made to input variables of a process so that we may observe and identify the changes in the output response [14]. Some of the design parameters are controllable, for example physical dimensions of a layout like dielectric layer thickness, transmission line width etc, whereas other variables, material properties like dielectric constant, are uncontrollable.

The objectives of the experiment include the following:

1. Determining which parameters are most influential on the performance measures.
2. Determining where to set the influential design parameters so that the performance specifications are almost always near the desired value.
3. Determining where to set the influential design parameters so that the effects of the uncontrollable variables are minimized.

Many experiments involve the study of the effects of two or more factors. In

general, factorial designs are most efficient for this type of experiment. By a factorial design, we mean that in each complete trial or replication of the experiment all possible combinations of the levels of the factors are investigated. For example, if there are  $a$  levels of factor A and  $b$  levels of factor B, then each replicate contains all  $a*b$  treatment combinations.

The effect of a factor is defined to be the change in response produced by a change in the level of the factor. This is frequently called a 'main effect' because it refers to the primary factors of interest in the experiment. In some experiments, we may find that the difference in response between the levels of one factor is not the same at all levels of the other factors. When this occurs, there is an interaction between the factors [18].

#### **2.4.1 Two level vs three level**

The simplest types of factorial designs [20] involve only two factors, i.e., all the input parameters are varied at two levels, minimum and maximum. Minimum and maximum values envelope the total range of values that a design parameter can take considering the process variations and tolerance [24]. This experiment is represented as  $2^k$  factorial design, where 2 represents the levels of each input parameter and  $k$  represents the number of input parameters. Another type of design is a factorial arrangement with  $k$  factors at three levels. Without loss of generality, we may refer to the three levels of factors as low, intermediate and high. This experiment is called  $3^k$  factorial design. Table 1 illustrates a  $3^k$  fractional factorial plan. In this experiment, the three levels are designated by the digits 0(low), 1(intermediate) and 2(high).

The  $3^k$  design is often considered when one is concerned about the curvature in the response function. The addition of a third level allows the relationship between the response and each factor to be modeled with a quadratic relationship. This is not possible with  $2^k$  plan. The  $3^k$  factorial plan is used in this thesis so that the nonlinear



**Table 1:** Array showing the full factorial plan

Experiment	A	B	C
1	0	0	0
2	1	0	0
3	2	0	0
4	0	1	0
5	1	1	0
6	2	1	0
7	0	2	0
8	1	2	0
9	2	2	0
10	0	0	1
11	1	0	1
12	2	0	1
13	0	1	1
14	1	1	1
15	2	1	1
16	0	2	1
17	1	2	1
18	2	2	1
19	0	0	2
20	1	0	2
21	2	0	2
22	0	1	2
23	1	1	2
24	2	1	2
25	0	2	2
26	1	2	2
27	2	2	2

relationship between the design parameters and the performance measures can be obtained. The main drawback of using  $3^k$  plan over  $2^k$  is that, with the increase in number of design parameters the number of experiments increase exponentially. This can be taken care by using fractional factorial plan of  $3^k$  experiments, which is explained below.

#### **2.4.2 Full factorial vs fractional factorial plan**

One way to plan the experiments is to simulate all combinations of the design factors at all levels. This is called the full-factorial experimentation. If  $m$  is the level of the experiment plan and  $n$  is the number of design parameters, full-factorial experiment results in  $m^n$  simulations. Depending on the number of design parameters, full-factorial approach may require a large number of simulations.

In many scientific investigations, the main interest is in the study of effects of many factors simultaneously. Factorial designs, especially two-level or three-level factorial designs, are the most commonly used experimental plans for this type of investigation. A full factorial experiment allows all factorial effects to be estimated independently. However, it is often too costly to perform a full factorial experiment, so a fractional factorial design [20], which is a subset or fraction of a full factorial design, is preferred since it is cost-effective.

In statistics, fractional factorial designs are experimental designs consisting of a carefully chosen subset (fraction) of the experimental runs of a full factorial design. The subset is chosen so as to exploit the sparsity-of-effects principle to expose information about the most important features of the problem studied, while using a fraction of the effort of a full factorial design in terms of experimental runs and resources. The *sparsity-of-effects* principle states that a system is usually dominated by main effects and low-order interactions. Thus it is most likely that main (single factor) effects and two-factor interactions are the most significant responses. In other

words, higher order interactions such as three-factor interactions are very rare.

Fractional designs are expressed using the notation  $l^{k-p}$ , where  $l$  is the number of levels of each factor investigated,  $k$  is the number of factors investigated, and  $p$  describes the size of the fraction of the full factorial used. Formally,  $p$  is the number of generators, assignments as to which effects or interactions are confounded, i.e., cannot be estimated independently of each other. A design with  $p$  such generators is a  $1/(l^p)$  fraction of the full factorial design.

### 2.4.3 Generating three level fractional ( $3^{k-p}$ ) factorial plans

A fractional factorial experiment is generated from a full factorial experiment by choosing an *alias structure* [30]. The alias structure determines which effects are confounded with each other. For example, the five factor fractional factorial plan ,  $3^{5-2}$  can be generated by using a full three factor factorial experiment involving three factors (say A, B, and C) and then choosing to confound the two remaining factors D and E with interactions generated by

$$x_4 = x_1 + x_2 + x_3 \pmod{3}, \quad x_5 = x_1 + 2x_2 \pmod{3} \quad (4)$$

Symbolically, we write  $D = ABC$  and  $E = AB^2$ . From Equation 4, by using modulus 3 arithmetic, we obtain

$$\begin{aligned} x_1 + x_2 + x_3 + 2x_4 &= 0 \pmod{3}, & 2x_1 + 2x_2 + 2x_3 + x_4 &= 0 \pmod{3} \\ x_1 + 2x_2 + 2x_5 &= 0 \pmod{3}, & 2x_1 + x_2 + x_5 &= 0 \pmod{3} \\ x_1 + 2x_3 + x_4 + x_5 &= 0 \pmod{3}, & 2x_1 + x_3 + 2x_4 + 2x_5 &= 0 \pmod{3} \\ x_2 + 2x_3 + x_4 + 2x_5 &= 0 \pmod{3}, & 2x_2 + x_3 + 2x_4 + x_5 &= 0 \pmod{3} \end{aligned} \quad (5)$$

Equivalently, we write

$$I = ABCD^2 = A^2B^2C^2D = AB^2E^2 = A^2BE = AC^2DE = A^2CD^2E^2 = BC^2DE^2 = B^2CD^2E \quad (6)$$

where  $I$  is the identity element and  $ABCD^2$ ,  $A^2B^2C^2D$ , etc. are called defining words. Each word represents a contrast with 2 degrees of freedom. Words  $ABCD^2$  and  $A^2B^2C^2D$  represent the same contrast because their corresponding equations  $x_1 + x_2 + x_3 + 2x_4 = 0(mod3)$  and  $2x_1 + 2x_2 + 2x_3 + x_4 = 0(mod3)$  are equivalent. To avoid ambiguity, the convention is to set the first non-zero coefficient to be 1. Then Eq 6 reduces to

$$I = ABCD^2 = AB^2E^2 = AC^2DE = BC^2DE^2 \quad (7)$$

which is called the *defining contrast subgroup* for the design. This design has one word of length three and three words of length four. The resolution is III because the shortest word has length 3. For a three-level design, a main effect has two degrees of freedom. Table 2 shows a  $3^{(5-2)}$  fractional factorial plan with 27 runs and 5 input parameters varied at 3 levels.

Since 10 design parameters are used in the test case, fractional factorial plan is used to simulate the DOE's. The time taken for simulation of each experiment and the comparison of full factorial and fractional factorial plan is shown in Figure 13. It can be clearly seen from the table that the simulation time is reduced by 2187 times if fractional factorial plan is used.

	10 parameter Fractional factorial	10 parameter Full factorial
Time taken for 1 simulation	540 secs	540 secs
Total number of simulations	$3^{10-7} = 27$	$3^{10} = 59049$
Total simulation time	4.05 hrs	8857.35 hrs

**Figure 13:** Comparison of fractional and full factorial plans.

**Table 2:** Fractional factorial design of 27 runs and 5 factors

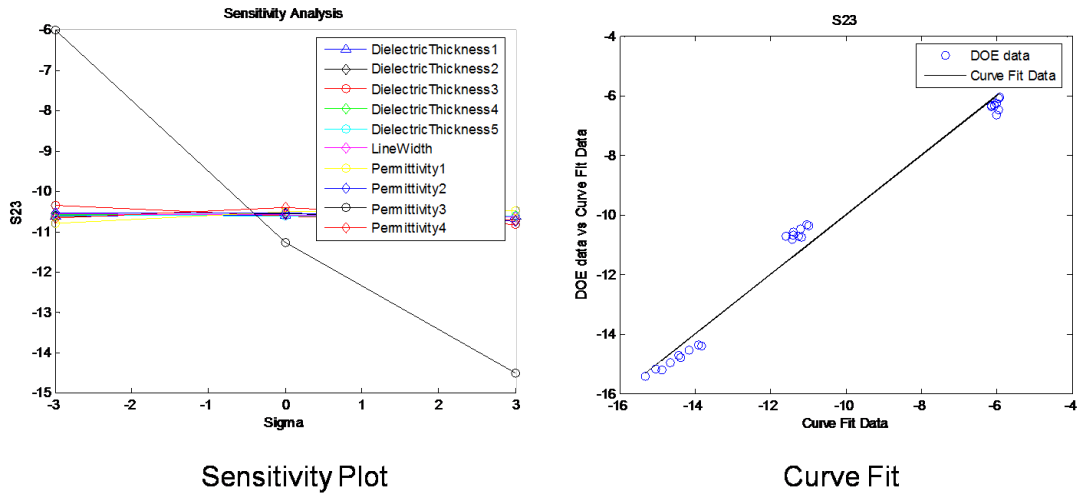
Experiment	A	B	C	$D=ABC$	$E=AB^2$
1	0	0	0	0	0
2	1	0	0	1	0
3	2	0	0	2	0
4	0	1	0	1	2
5	1	1	0	2	2
6	2	1	0	0	2
7	0	2	0	2	1
8	1	2	0	0	1
9	2	2	0	1	1
10	0	0	1	1	1
11	1	0	1	2	1
12	2	0	1	0	1
13	0	1	1	2	0
14	1	1	1	0	0
15	2	1	1	1	0
16	0	2	1	0	2
17	1	2	1	1	2
18	2	2	1	2	2
19	0	0	2	2	2
20	1	0	2	0	2
21	2	0	2	1	2
22	0	1	2	0	1
23	1	1	2	1	1
24	2	1	2	2	1
25	0	2	2	1	0
26	1	2	2	2	0
27	2	2	2	0	0

## 2.5 Sensitivity Analysis

Sensitivity analysis is a technique used to determine how different values of an independent variable (design parameters) will impact a particular dependent variable (performance measures) under a given set of assumptions [14]. Sensitivity analysis is very useful when attempting to determine the impact the actual outcome of a particular variable will have if it differs from what was previously assumed. By creating a given set of scenarios, the analyst can determine how the changes in input parameters will impact the performance measures.

Table 2 shows the fractional factorial DOE's with the entries being 0's, 1's and 2's. Elements of this matrix are coded values of the parameters where 1s represent their mean ( $\mu$ ), 0 and 2 are  $\mu - 3\sigma$  and  $\mu + 3\sigma$ . Each row represents a different simulation condition. The sensitivity plots for these experiments can be obtained by averaging the response (performance measure) at each level of the input parameter. The plots are plotted with the x-axis ranging from  $\mu - 3\sigma$  and  $\mu + 3\sigma$  for each parameter. Slopes of the curves indicate sensitivity of the performance measures to the associated design parameter. The next section deals with the regression analysis.

Figure 14 shows the sensitivity plot and the curvefit plot for the test case.



**Figure 14:** Sensitivity analysis and curvefit plots.

## 2.6 Regression analysis

Generally based on the linearity of these plots, the performance measures can be represented as either first order linear approximations or include both first order, second order and interaction terms to the regression expression [17]. If the expression with all the three types of terms, namely first order, second order and interaction terms, are taken into account, then the regression expression is as shown in the Equation 8

$$P^i = \beta_0 + \sum_{i=1}^n \beta_i x_i + \sum_{i=1}^n \sum_{j=1}^n \beta_{ij} x_i x_j + \varepsilon \quad (8)$$

where  $P^i$  is the approximated response,  $x$ 's are design parameters,  $\beta_0$  is the intercept term,  $\beta_i$ 's are the coefficients of the first-order effects,  $\beta_{ij}$  are the coefficients of the second-order effects and  $\epsilon$  is the approximation error. If  $i \neq j$ , then  $\beta_{ij}$  is called the interaction coefficient.

This expression, by default, is used to curvefit the DOE experiment data. For the case with 3 input parameters and 2 performance measures, the expression can be written as

$$P = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_{12} x_1 x_2 + \beta_{23} x_2 x_3 + \beta_{31} x_3 x_1 + \beta_{11} x_1^2 + \beta_{22} x_2^2 + \beta_{33} x_3^2 + \varepsilon \quad (9)$$

where  $P$  is the approximated response vector,  $x$ 's are design parameters,  $\beta_0$  is the intercept vector,  $\beta_i$ 's are the vector coefficients of the first-order effects,  $\beta_{ij}$  are the vector coefficients of the second-order effects and  $\epsilon$  is the approximation error vector.

Most of the times, the curvefit data will have some error associated with it when compared to the DOE simulation data. This might be due to the non linear relation between the performance measures and the design parameters. The level of error in the curvefit can be obtained by a statistical term known as *Regression coefficient*.  $R^2$

represents the regression coefficients, a measure of model fitness, and is computed as

$$R^2 = 1 - \frac{\sum_1^{27} [\varepsilon_i]^2}{\sum_1^{27} [P^i - \bar{P}^i]^2} \quad (10)$$

$R^2$  values close to 1 indicate good predictive capability of the regression equations.

Figure 15 shows the response surface plot for the test case.

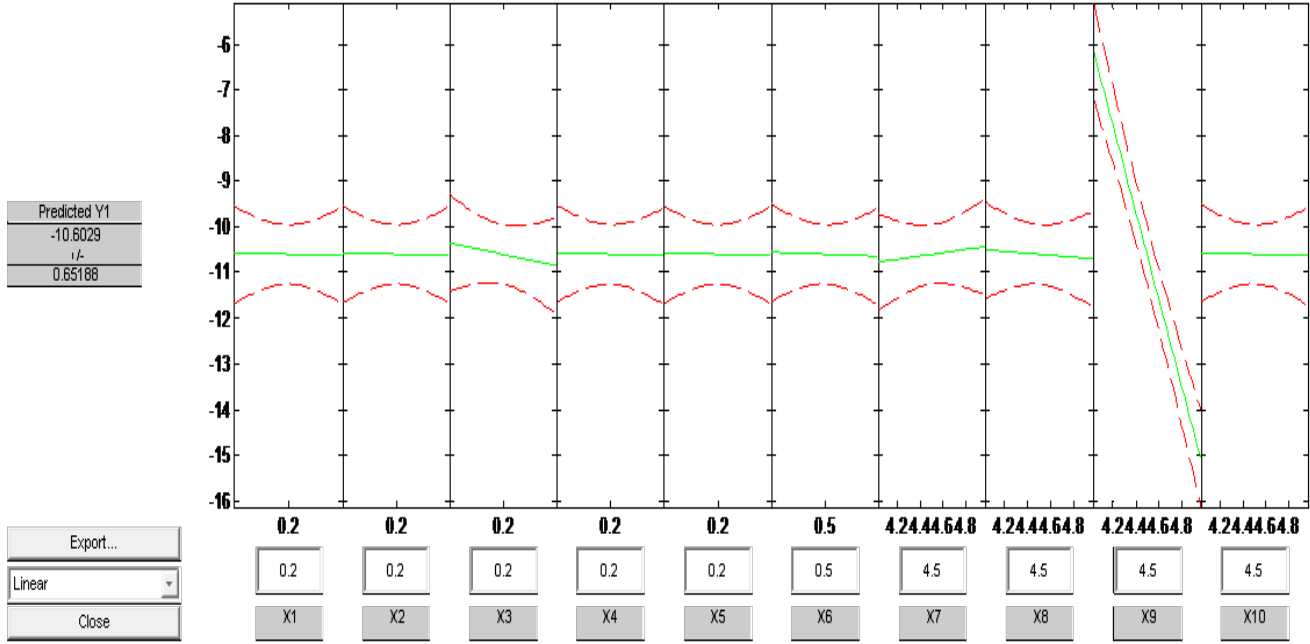


Figure 15: Response surface plot.

## 2.7 Convolution and probability density functions

Components constituting a large digital system are usually manufactured separately. Therefore, their statistical variations can be assumed independent of each other. In this dissertation, it is assumed that the design parameters are Gaussian distributed. Using the probability density functions of the design parameters and the Equations 8, the probability density functions (pdf) of the performance measures can be computed [21]. This provides a significant advantage in reflecting their variations to the performance. For the general case, let  $y$  be a random variable defined as:



$$y = y_0 + h_1(x_1) + h_2(x_2) + h_3(x_3) + \dots + h_n(x_n) \quad (11)$$

where  $h_1, h_2, \dots, h_n$  are functions of the independent random variables  $x_1, x_2, \dots, x_n$ .

Then *pdf* of  $y$  is defined as

$$f_y(y) = \delta(y - y_0) \otimes f_{h_1}(h_1(x_1)) \otimes f_{h_2}(h_2(x_2)) \otimes \dots \otimes f_{h_n}(h_n(x_n)) \quad (12)$$

where  $\delta$  is the delta function,  $\otimes$  is the convolution operator and  $f_{h_1}(h_1(x_1)), \dots, f_{h_n}(h_n(x_n))$  are the *pdfs* of  $h_1(x_1), \dots, h_n(x_n)$  respectively. Given the *pdf* of a random variable  $x_k$ ,  $f_{x_k}(x_k)$ , and a function  $h_k(x_k)$ , the *pdf* of the random variable  $h_k$  can be computed as

$$f_{h_k}(h_k) = \frac{f_{x_k}(x_{k1})}{|\dot{h}_k(x_{k1})|} + \frac{f_{x_k}(x_{k2})}{|\dot{h}_k(x_{k2})|} + \dots + \frac{f_{x_k}(x_{kn})}{|\dot{h}_k(x_{kn})|} \quad (13)$$

where  $x_{k1}, x_{k2}, \dots, x_{kn}$  are solutions to the equation  $h_k - \dot{h}_k(x_k) = 0$  for a specific value of  $h_k$ , and  $\dot{h}_k$  is the derivative of  $h_k$ . For cases where  $\beta_k$  is the coefficient from the regression equation. Then we have

$$f_{h_k}(h_k) = \frac{f_{x_k}(h_k/\beta_k)}{|\beta_k|} \quad (14)$$

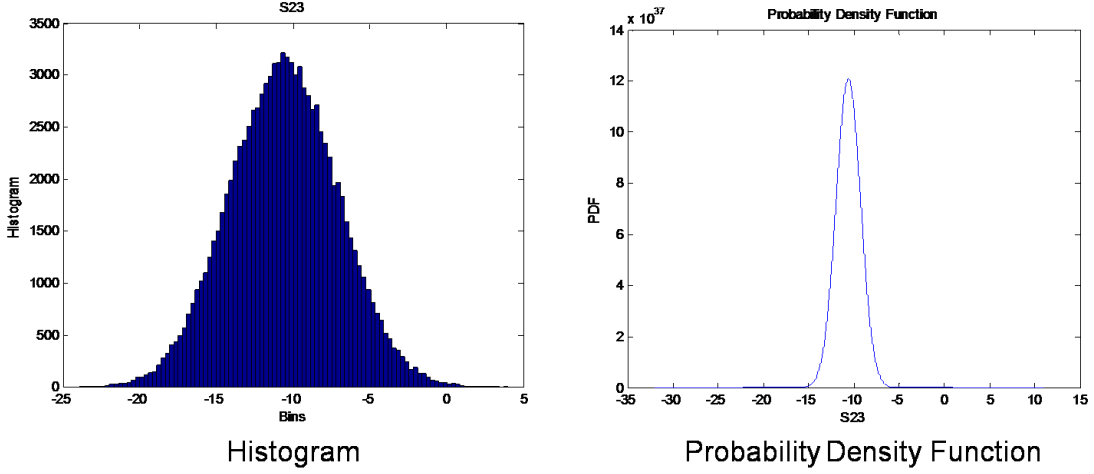
Therefore, the *pdfs* of the performance measures can be computed by convolving the *pdfs* of the summation terms in (8) as shown

$$f_{P^i}(P^i) = \delta(P^i - \beta_{i0}) \otimes f(\beta_{i1}X1) \otimes f(\beta_{i2}X2) \otimes \dots \otimes f(\beta_{in}Xn) \quad (15)$$

Figure 16 shows the histogram and probability density function for the performance specification  $S_{23}$  for the test case.

## 2.8 Yield estimation/optimization

For explaining the diagnosis approach, let  $[X]$  and  $[Y]$  be the random vectors for  $n$  layout parameters and  $m$  performance measures, respectively. The functional relation between  $[X]$  and  $[Y]$  is obtained by characteristic DOE-based simulations. If  $n$



**Figure 16:** Histogram and probability density function.

is greater than  $m$ , then a unique solution of  $[X]$  does not exist for a measured set of unacceptable performance metrics  $[Y]$ . Hence, the real parameter(s) causing the failure cannot be *accurately* decided. However since all design parameters are associated with *pdfs*, the most probable solution can be searched. The conditional *pdf* of the parameter vector  $[X]$  for measured performance  $y$  is defined

$$f(X|Y = y) = \frac{f(X, Y)}{f(Y)} \quad (16)$$

where  $f(X, Y)$  is the joint *pdf* (*jpdf*) of the random vector of the design parameters and performance measures  $[X^T Y^T]^T$ . Then, the expected value of  $f(X|Y = y)$  is the most probable parameter set causing the failure. Let  $\tilde{Y} = [P^1, P^2, \dots, P^m]^T$  be the set of unacceptable performance measures. Equations for the performance measures can be rewritten by subtracting the intercept term as follows  $\beta_{10}, \beta_{20}, \dots, \beta_{n0}$  from  $\tilde{Y}$  resulting in

$$Y = \beta X + \varepsilon \quad (17)$$

where  $X$  is the parameter column, and  $Y, \beta$  and  $\varepsilon$  are defined as

$$Y = \begin{bmatrix} P^1 - \beta_{10} \\ P^2 - \beta_{20} \\ \dots\dots\dots \\ P^n - \beta_{n0} \end{bmatrix} \quad \beta = \begin{bmatrix} \beta_{11}\beta_{12}\dots\dots\beta_{1k} \\ \beta_{21}\beta_{22}\dots\dots\beta_{2k} \\ \dots\dots\dots \\ \beta_{n1}\beta_{n2}\dots\dots\beta_{nk} \end{bmatrix} \quad \varepsilon = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \dots \\ \varepsilon_n \end{bmatrix} \quad (18)$$

The error column  $\epsilon$  is a gaussian random vector with a zero mean computed from the approximation errors. Since  $X$  and  $Y$  are gaussian random vectors, a new random vector  $Z$  can be defined as  $Z_{n \times 1} = [X^T Y^T]^T$ . Then, the *pdf* of  $Z$  is equivalent to the *jpdf* of  $X$  and  $Y$ , which can be computed as

$$f_Z(Z) = f_{X,Y}(X, Y) = \frac{\text{Exp}\{-1/2([Z] - E[Z])^T \text{Cov}(Z)^{-1}([Z] - E[Z])\}}{(2\pi)^2 |\text{Cov}(Z)|^{1/2}} \quad (19)$$

where  $E[Z] = [\mu_X^T, \mu_Y^T]^T$ , and  $\text{Cov}(Z)_{n \times n}$  is a matrix composed of covariance matrices [10] of  $X$  and  $Y$  vectors given by

$$\text{Cov}(Z) = \begin{bmatrix} \text{Cov}(X, X) & \text{Cov}(X, Y) \\ \text{Cov}(Y, X) & \text{Cov}(Y, Y) \end{bmatrix} \quad (20)$$

It is important to note that for independent design parameters,  $\text{Cov}(X, X)$  is the diagonal matrix of the parameter variances. The expected value of the conditional *pdf* in Equation 16 can be computed as

$$E[X|Y = y] = \mu_X + \text{Cov}(X, Y)[\text{Cov}(Y, Y)]^{-1}(Y - \mu_Y) \quad (21)$$

Since  $X$  and  $Y$  are related through the linear regression operator, defined in Equation 17, as  $Y = \beta X + \epsilon$ , then

$$\mu_Y = \beta \mu_X \quad (22)$$

$$Cov(X, Y) = Cov(X, X)\beta^T \quad (23)$$

$$Cov(Y, Y) = \beta Cov(X, X)\beta^T + Cov(\varepsilon) \quad (24)$$

where  $Cov(\varepsilon)$  is the covariance matrix of the error vector in Equation 17. Substitution of Equations 22 through 24 results in

$$E[X|Y = y] = \mu_X + Cov(X, X)\beta^T[\beta Cov(X, X)\beta^T + Cov(\varepsilon)]^{-1}(Y - \beta\mu_X) \quad (25)$$

Figure 17 shows the parametric average yield value for the test case. The boundary values taking regression error into account also can be seen in the table.

<b>Output Yield %</b>	<b>54.82</b>
<b>Minimum output yield%</b>	<b>54.71</b>
<b>Maximum output yield%</b>	<b>54.94</b>

**Figure 17:** Parametric average yield value and the boundary yield values.

## 2.9 Design Centering

Design centering is a process which when applied to the input parameters improves the output yield value [28] [29]. The methodology used in this dissertation is a simple weighted average method. After calculating the yield output, all the experiments from the DOEs, which satisfy the given performance specifications, are collected. The values of the input parameters used to simulate the DOE's are taken and the average value is calculated. These averaged values will form the set of design centered values for the input parameters.

Figure 18 shows the parametric average yield value for the test case. The boundary values taking regression error into account also can be seen in the table.

<b>Diel1</b>	<b>Diel2</b>	<b>Diel3</b>	<b>Diel4</b>	<b>Diel5</b>	<b>Line Width</b>	<b>Er1</b>	<b>Er2</b>	<b>Er3</b>	<b>Er4</b>
0.2	0.2	0.2	0.2	0.2	0.5	4.5	4.5	4.5	4.5
0.2	0.2	0.2	0.2	0.2	0.5	4.5	4.73	4.5	4.5

**Figure 18:** Nominal and design centered values.

## ***2.10 Summary***

In this chapter, the modeling and formulation of the statistical analysis is discussed. Different steps involved in the analysis like choosing the design of experiments, sensitivity analysis, regression analysis and curvefit, probability distribution functions, joint probability distribution function, yield output and design centering are discussed. The mathematical formulation in arriving at the final solution is provided.

## CHAPTER III

### RESULTS

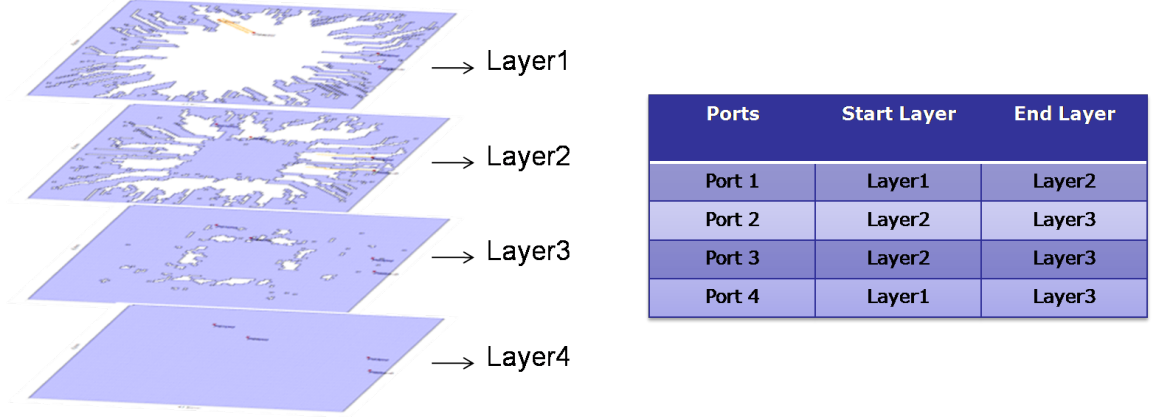
In this chapter, three test cases are presented. The first test case is a 4 layer package and the performance specifications look into the signal integrity of the package by choosing the insertion loss parameters as performance measures. The design of experiments are created in both full factorial plan and fractional factorial plan for 5 design parameters. Simulation is done and the results are presented. Both full factorial plan and fractional factorial plan give out similar results. Hence, the use of fractional facctorial plan is validated. Design centered values of the input parameters are given out.

The second test case is an RF bandpass filter. Four input parameters are chosen and design of experiments are created. Statistical analysis is applied and the results are presented. A panel of filters are fabricated with process variations. They are measured and the output yield value is calculated with the same specifications as applied to the simulation part. The results are tabulated and the methodology is validated.

The third test case is DFM for wirebonds. Three input parameters are chosen and full factorial design of experiments are created. The results obtained by applying the statistical analysis are presented.

#### ***3.1 Test case 1 - Four layer package***

The test case consists of 4 layers as shown in Figure 19. Two transmission lines are present on Layer1 and two more lines are present on Layer2 (shown in Figure 20). Four ports are connected at the ends of the transmission lines. Table in Figure 19 shows the layer numbers between which the ports are connected.



**Figure 19:** Four Layer package and port locations

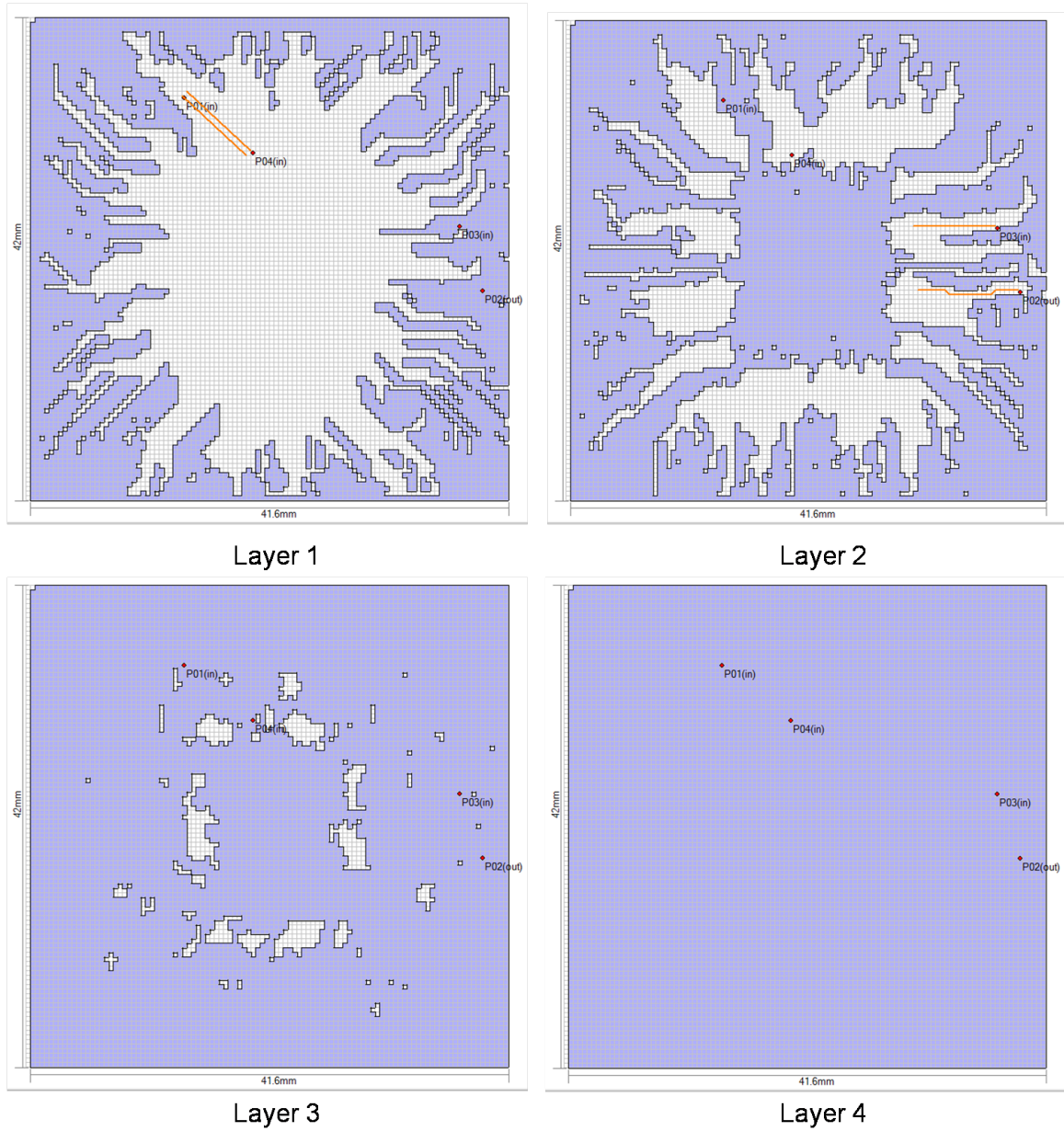
The simulation of the package layout is done using Mixed Signal Design Tools(MSDT-1). Frequency range of 1 Mhz to 5 Ghz is used for the simulation purposes. The insertion loss between the ports 1 and 4 -  $S_{14}$ , 2 and 4 -  $S_{24}$  are considered as performance specifications for this test case. The frequency response plots of  $S_{14}$  and  $S_{24}$  are shown in Figures 21 and 22 respectively. The performance specifications are as follows:

$$\begin{aligned}
 S_{14} &< -15db \\
 S_{24} &< -25db
 \end{aligned}
 \tag{26}$$

Five design parameters are selected for the test case. The design parameters chosen are the following:

1. Dielectric permittivity between layers 1 and 2 *Permittivity1*
2. Permittivity between layers 2 and 3 *Permittivity2*
3. Line Width of the transmission lines - *LineWidth*
4. Dielectric thickness between layers 1 and 2 *DielectricThickness1*
5. Dielectric thickness between layers 2 and 3 *DielectricThickness1*

Both full factorial plan and fractional factorial plan are used to simulate this test case. The number of simulations done for full factorial plan is  $3^5 = 243$ , while the



**Figure 20:** Four Layer package



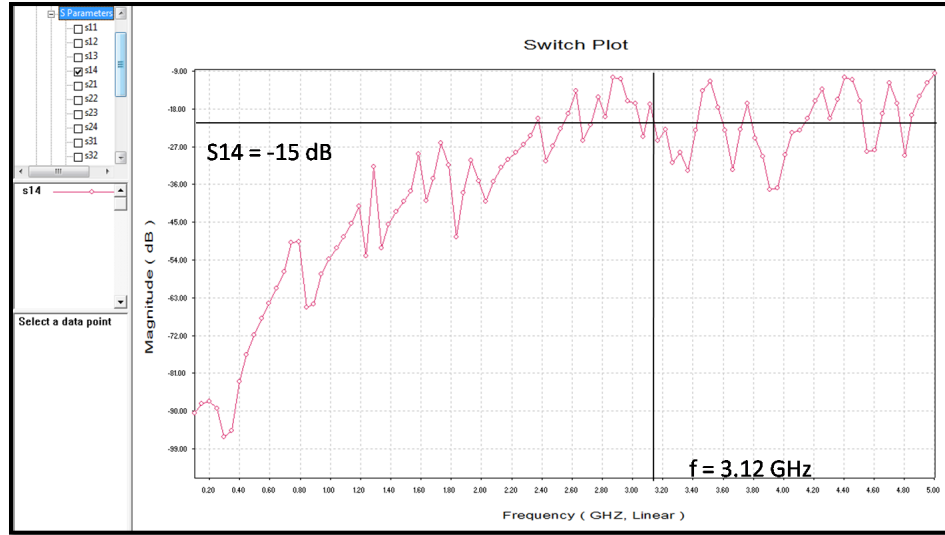


Figure 21: Performance Specification for insertion loss  $S_{14}$

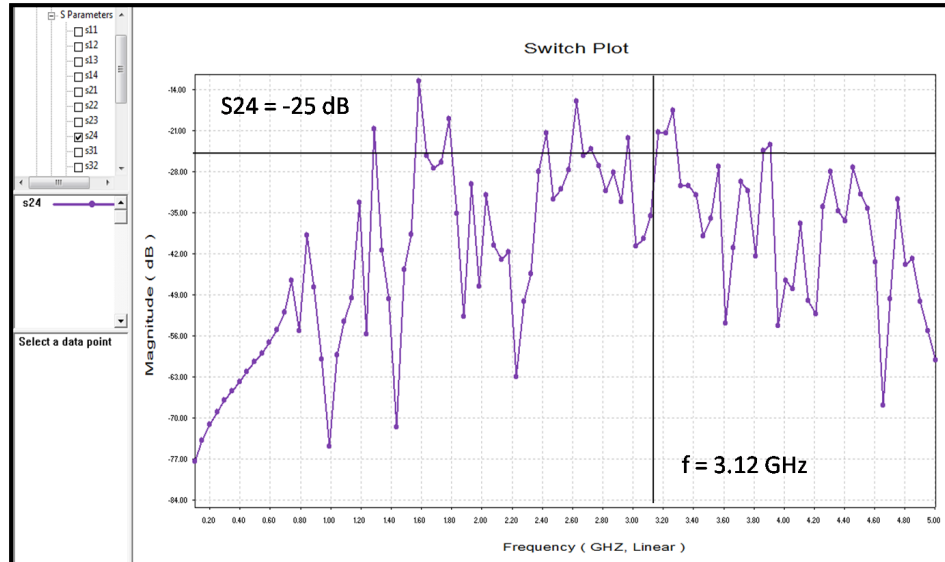


Figure 22: Performance Specification for insertion loss  $S_{24}$

	Full Factorial Plan	Fractional factorial Plan
Number of design parameters	5	5
Number of DOE's	243	81
Simulation time for one experiment (MSDT-1)	130 secs	130 secs
Total Simulation time (MSDT-1)	8.775 hrs	2.925 hrs

**Figure 23:** Comparison of Full factorial and fractional factorial plans

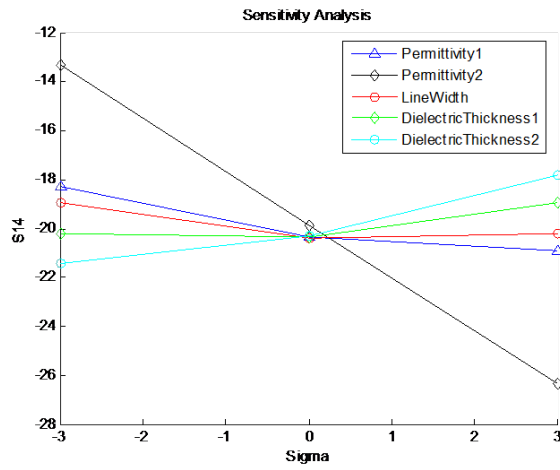
experiments used for fractional factorial plan are  $3^{(5-2)} = 27$ . Figure 23 gives the comparison of the total simulation time for both the cases. It can be clearly seen that fractional factorial plan is 9 times faster than the full factorial plan.

Figures 24 and 25 show the sensitivity plots of  $S_{14}$  and  $S_{24}$  respectively. Sensitivity analysis shows the variation of the performance measures when the design parameters are varied. Hence, the plots can be used to identify the significant/critical design parameters that can affect the performance of the package when varied.

While creating the design of experiments (DOE's), the input parameters are varied at 3 levels. Let's suppose those levels as -3, 0 and 3. The Sigma on x-axis in the plots represents the 3 levels. Since all the design parameters are represented in the same plot, Sigma notation is used instead of using the original values of the design parameters.

From the Figure 24, it can be seen that there is a linear relation between all the design parameters and the performance measure  $S_{14}$ . The maximum variation in the performance measure is seen when the input parameter Permittivity2 is varied. Hence, this is the critical input parameter in case of  $S_{14}$ .

Similarly from Figure 25, it can be seen that there is a non linear variation of the performance measure  $S_{24}$  with respect to the input parameters Permittivity1 and Permittivity2. Hence, if linear modeling is used in regression then there will be error in the regression analysis. Hence, non linear modeling should be used. In other words, second order terms and interaction terms should be used in regression expression.



Full Factorial DOE's

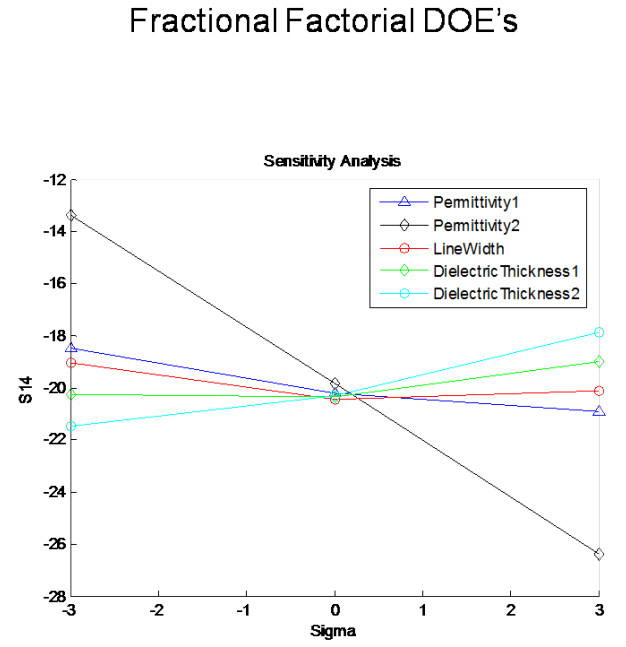
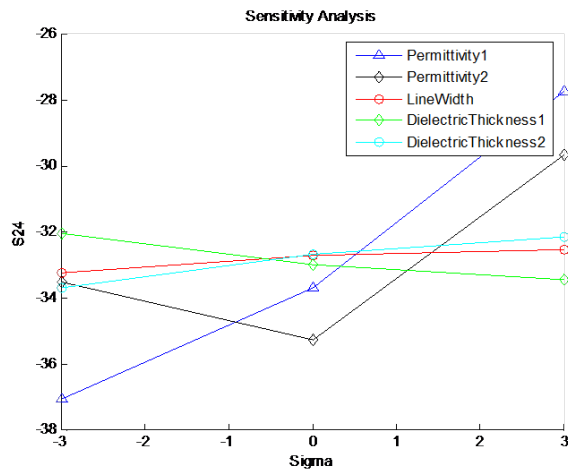


Figure 24: Sensitivity plot for insertion loss  $S_{14}$



Full Factorial DOE's

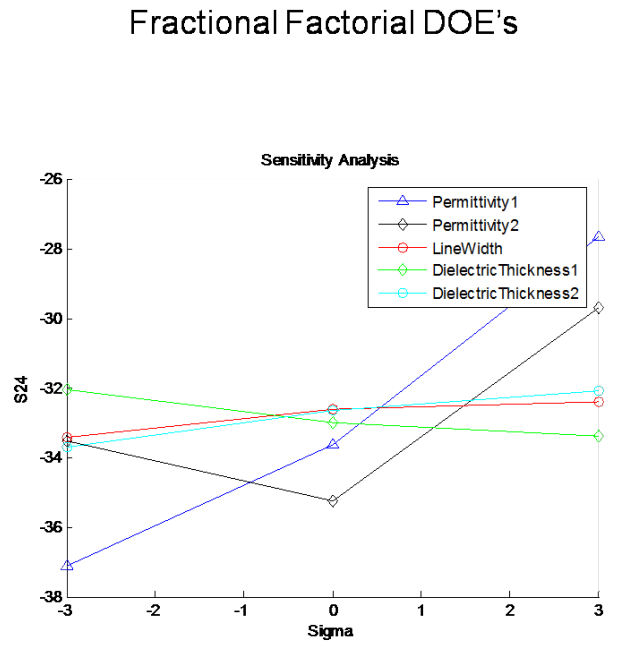
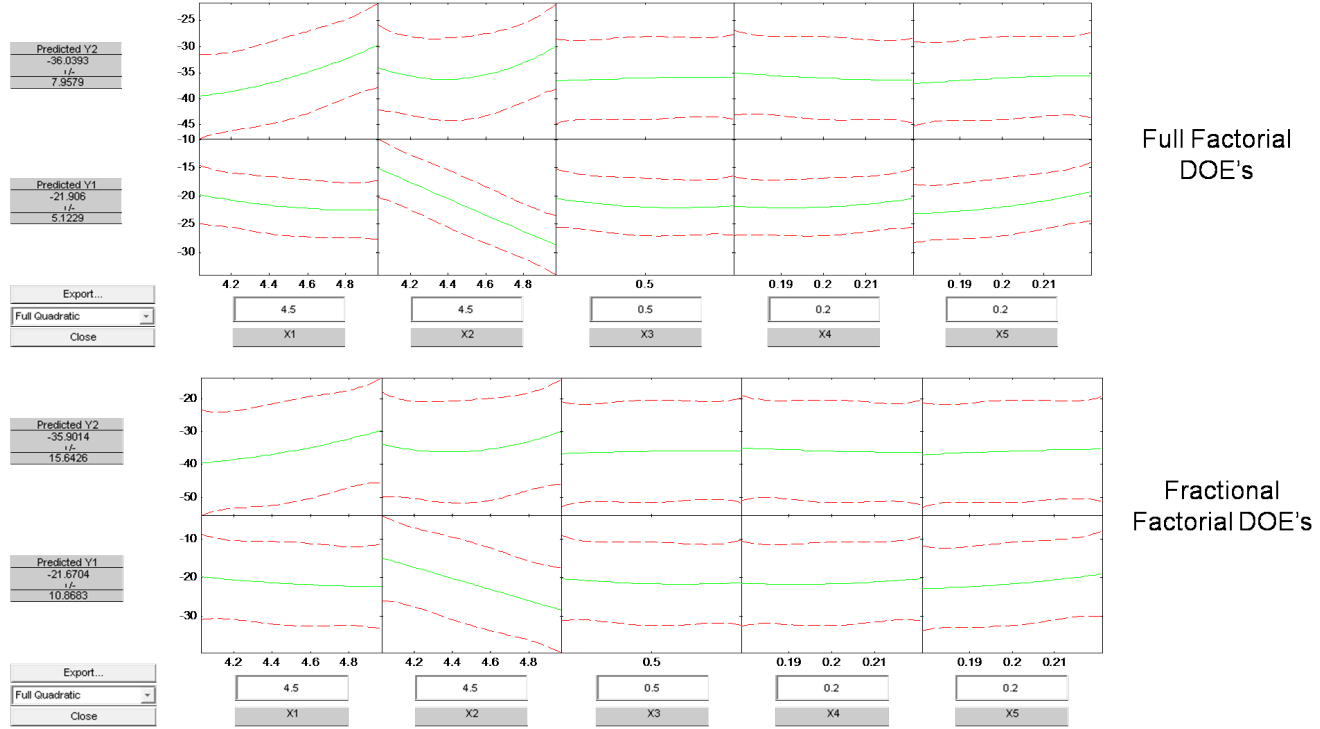


Figure 25: Sensitivity plot for insertion loss  $S_{24}$

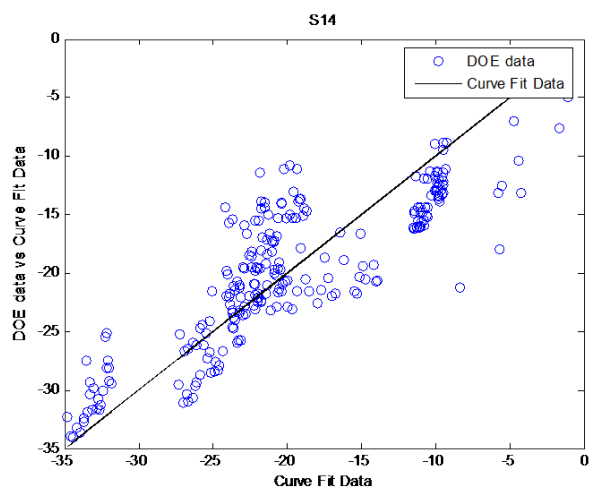


**Figure 26:** Response Plot

Figure 26 shows the response plot. It is a collection of all the sensitivity plots where the user can change the input parameter levels and observe the change in the performance measures [25]. This can help the user to know the starting point and direction of design centering. The green curves in the plot represent the regression fit and 2 red curves show the boundaries of the regression fit by taking regression coefficient into account.

The curve fit plot shows the DOE data and the regression fitted data against the regression fit data. This plot will show the error in the regression fit. Figures 27 and 28 show the curvefit of  $S_{14}$  and  $S_{24}$  respectively. If we look at both the curvefit plots, it can be seen that the fractional factorial experiments simulate a part of experiments present in a simulation environment. The same scattering pattern of experiments can be observed in both full factorial and fractional factorial plans, except that the density of experiments is less in case of fractional factorial plan.

Figures 29 and 30 show the histograms of  $S_{14}$  and  $S_{24}$  respectively. Histogram



Full Factorial DOE's

### Fractional Factorial DOE's

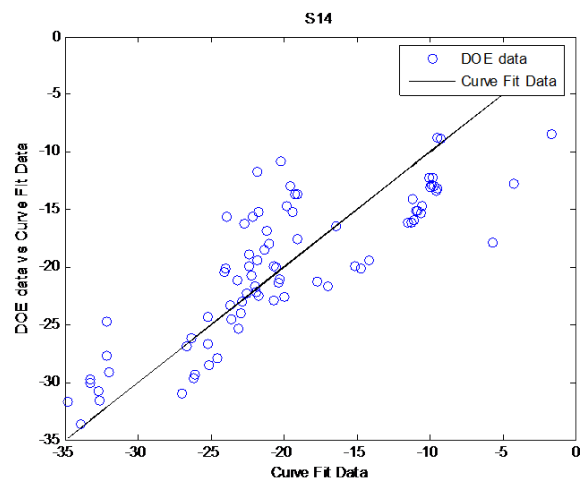
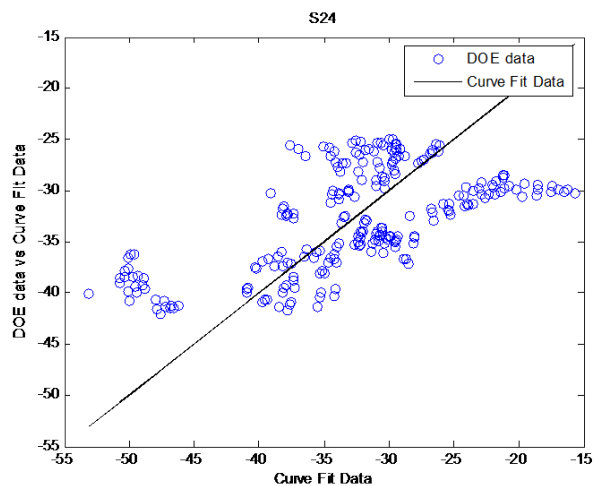


Figure 27: Curvefit plot for insertion loss  $S_{14}$



Full Factorial DOE's

### Fractional Factorial DOE's

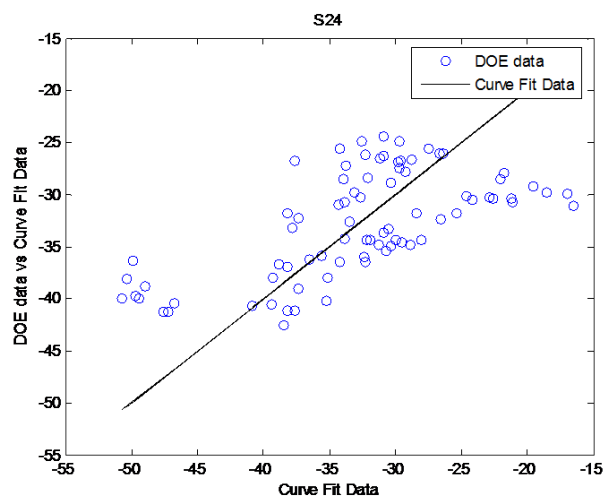
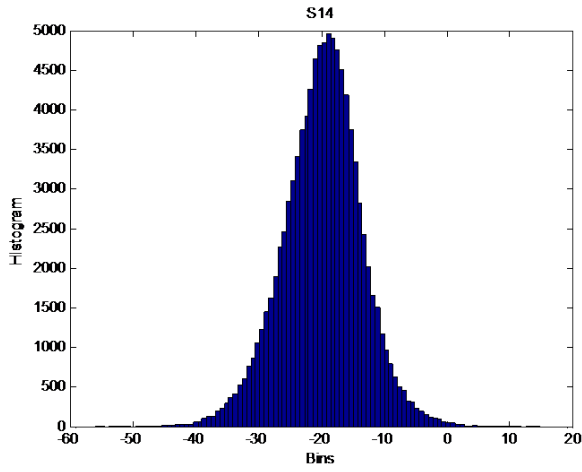


Figure 28: Curvefit plot for insertion loss  $S_{24}$



Full Factorial DOE's

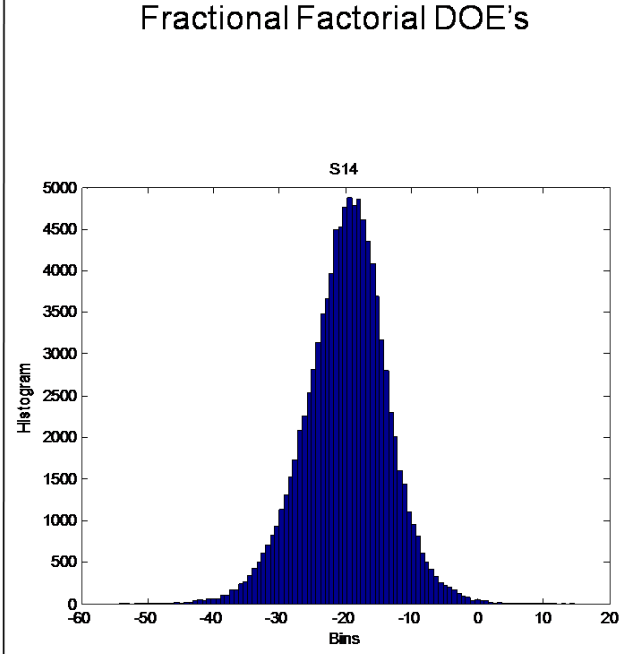
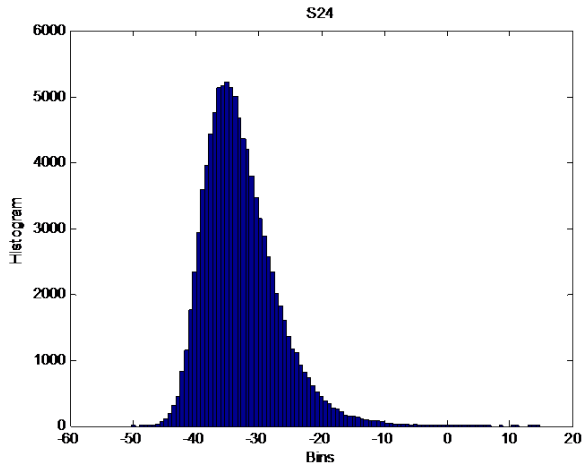


Figure 29: Histogram for insertion loss  $S_{14}$



Full Factorial DOE's

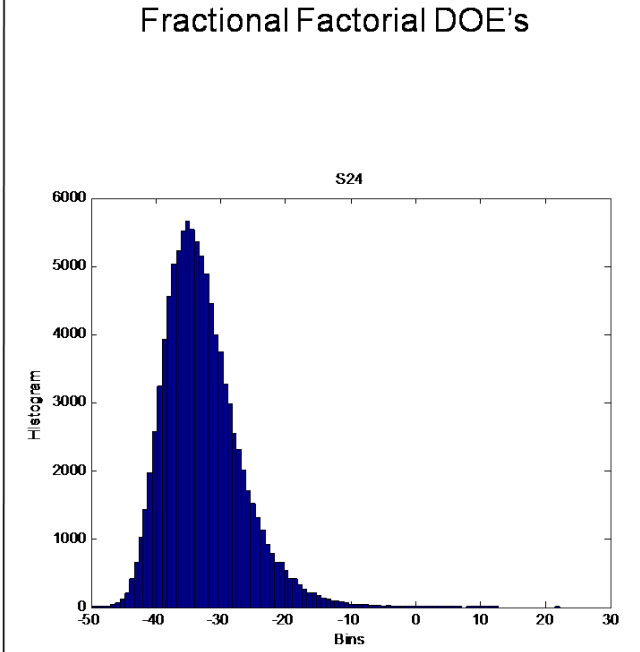
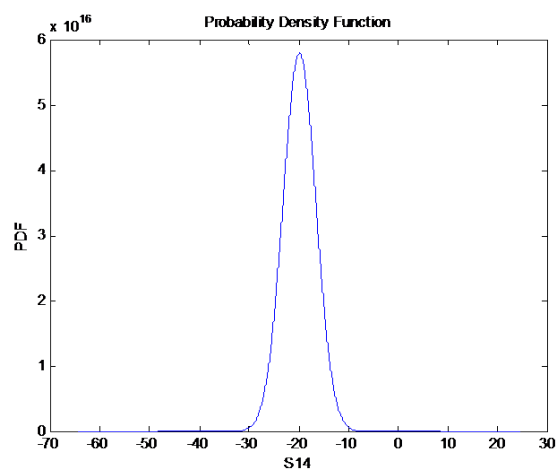


Figure 30: Histogram for insertion loss  $S_{24}$



Full Factorial DOE's

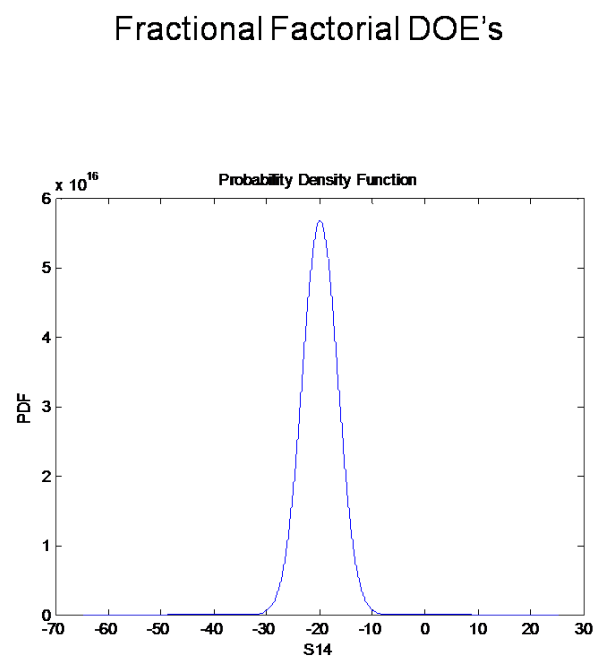
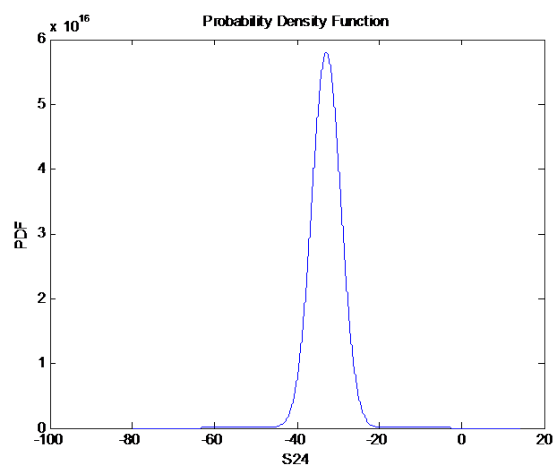


Figure 31: Probability density function plot for  $S_{14}$



Full Factorial DOE's

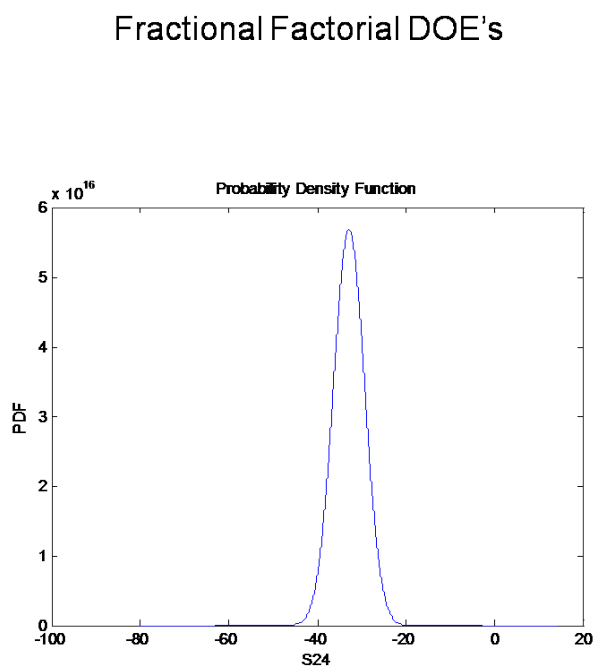
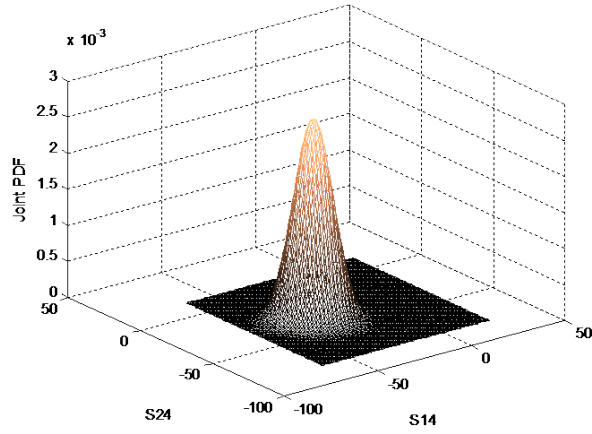


Figure 32: Probability density function plot for  $S_{24}$



Full Factorial DOE's

Fractional Factorial DOE's

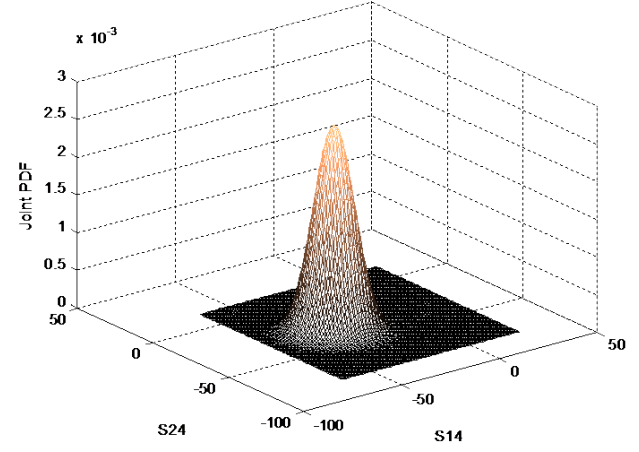


Figure 33: Four Layer package

plots show the distributed bins of the convoluted experiments.

The PDF's of each of the performance measure show the Gaussian distribution of the convoluted experiments obtained from coefficients of the regression analysis. Figures 31 and 32 show the *pdf*'s of  $S_{14}$  and  $S_{24}$  respectively.

The Joint probability distribution function is the combined Gaussian distributions of all the PDF's of the performance measures. JPDF is used in calculating the output yield value. Figure 33 shows the Joint *pdf* of the performance measures.



		Full Factorial Plan	Fractional Factorial Plan
Output Yield %		59.36	59.25
Minimum output yield%		55.70	55.70
Maximum output yield%		63.02	62.79
Line Width	0.50	0.501056	0.500000
Dielectric Thickness 1	0.20	0.200282	0.200426
Dielectric Thickness 2	0.20	0.197606	0.197447

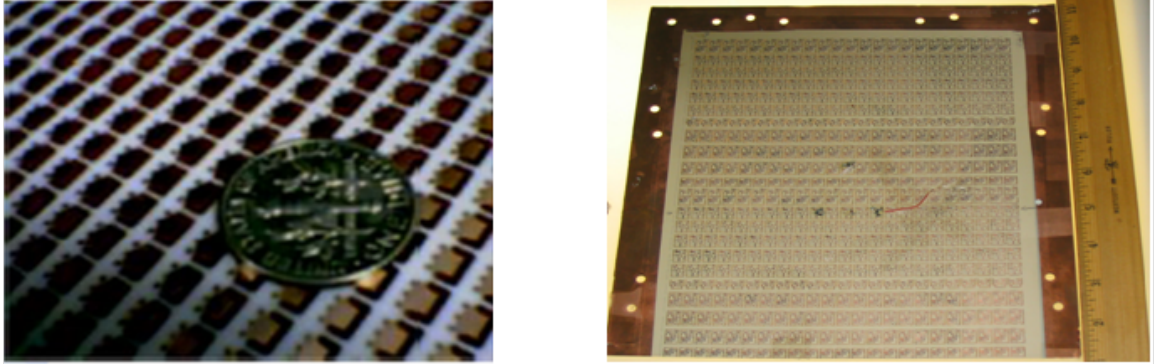
**Figure 34:** Output yield and design centering

Figure 34 shows the parametric output yield value and the design centered [9] values for the input parameters to optimize the output yield.

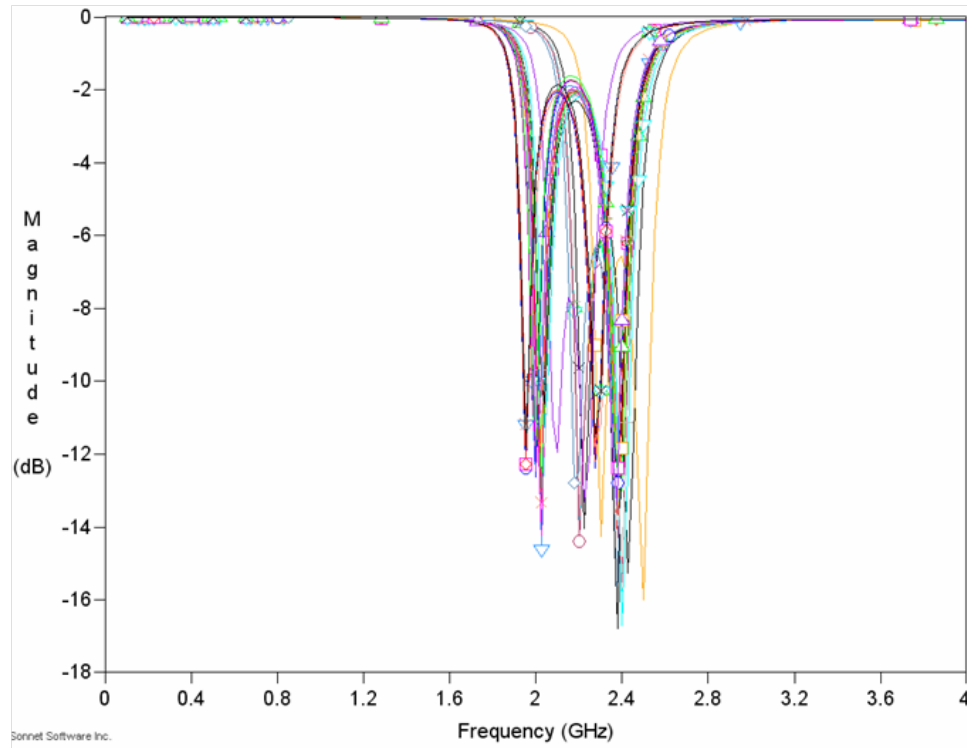
### ***3.2 Test case 2 - RF bandpass filter***

The focus of this test case is the application of statistical methods that enable accurate and efficient diagnosis of batch-fabricated RF circuits layouts[21]. For realistic yield estimation in batch fabrication, evaluation of the statistical analysis of performance measures is important. The picture of LCP[27] panel with bandpass filters is shown in Figure 35 [16] [8]. The panel consists of 2,000 RF bandpass filters. The spread of the performance measures (S21 and S11) for 50 such functional filters from the panel are shown in Figures 36 and 37. Due to the process variations, only a portion of the batch-fabricated filters meet the allowed range of specifications. The rest of the designs either depict functional failures (i.e. they do not possess filtering property), or they exhibit parametric failures (i.e. they show large variations in performance measures).

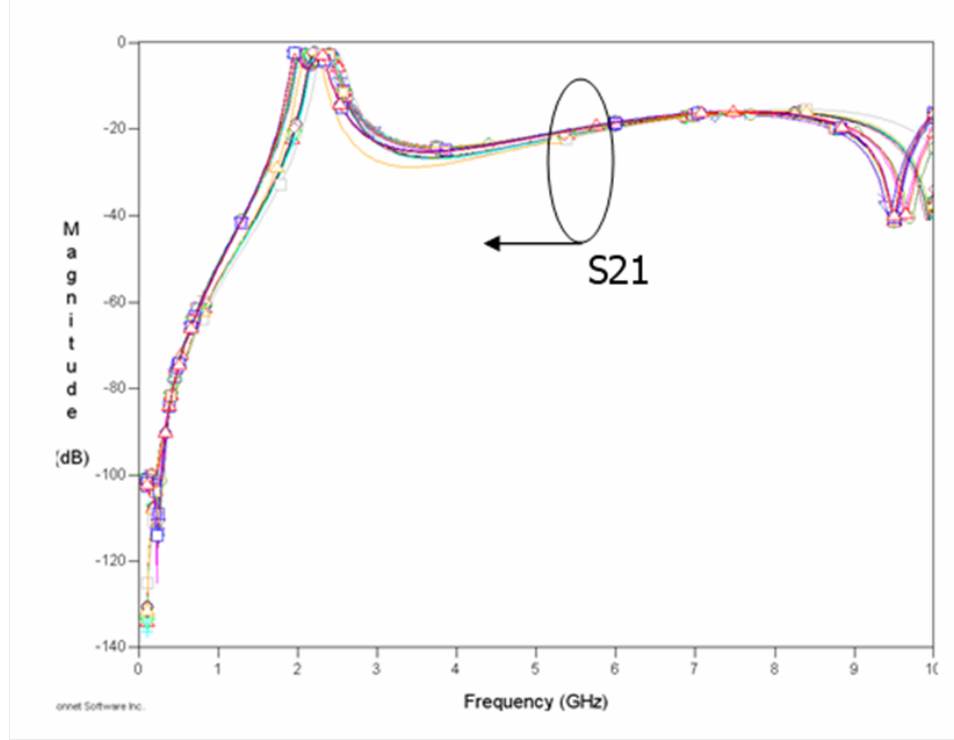
The filter layout (as seen in Sonnet) is shown in Figure 38. The RF bandpass filter is an important block in the design of an RF front end. With the convergence



**Figure 35:** (Left) Visual comparison of the filter size and (right) photograph of an LCP panel.



**Figure 36:** Measurement results of insertion loss (S11) for the fabricated filters.



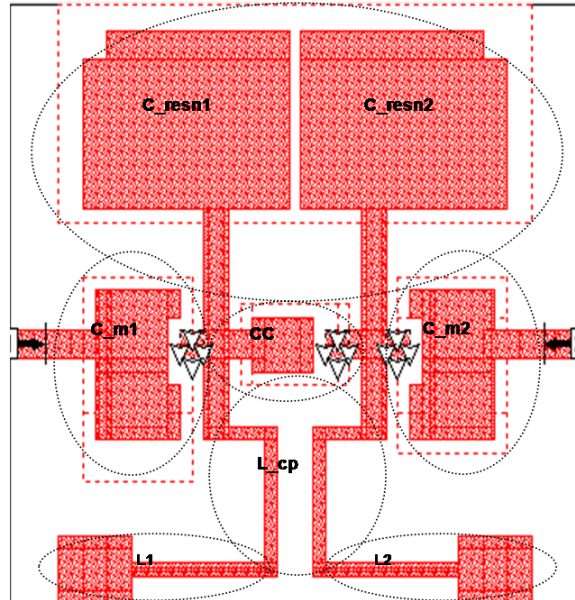
**Figure 37:** Measurement results of insertion loss ( $S_{21}$ ) for the fabricated filters.

of multiple frequency standards, the design of filters requires precise controllability of passband ripple, bandwidth, stopband attenuation and harmonic rejection. An example of the different performance measures for an RF bandpass filter is shown in Figure 39.

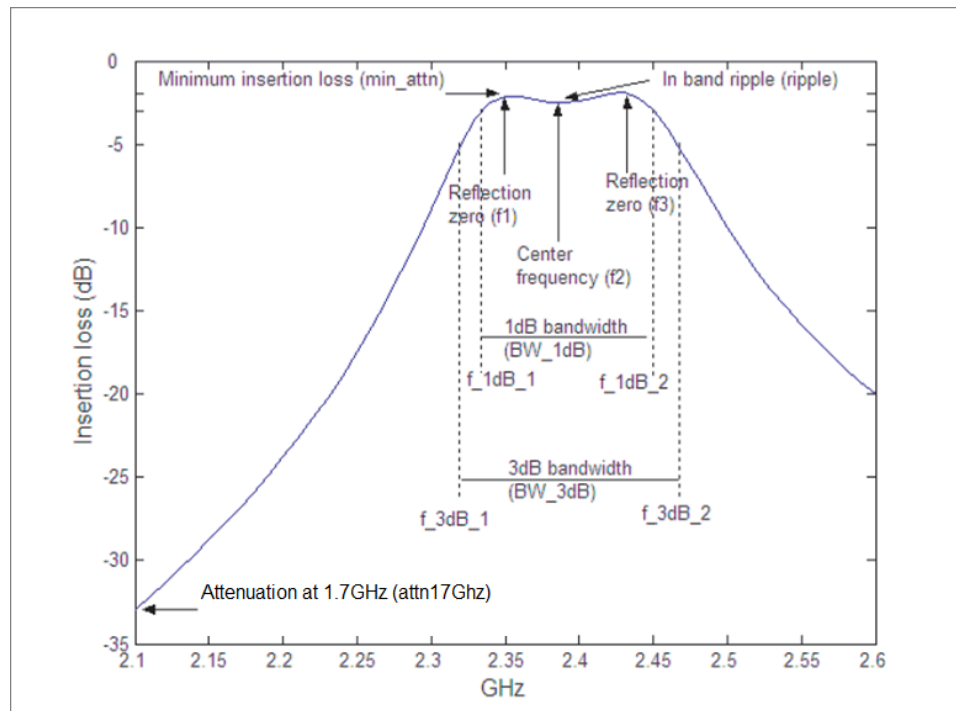
The design parameters chosen for this test case and their respective nominal values and the tolerance% values used for the EM simulations are as follows:

1. Resonator Capacitance Width - 51 mils - 11.76%
2. Matching Capacitance Width - 18 mils - 16.67%
3. Resonator Inductance Length - 36 mils - 8.33%
4. Dielectric Constant - 3.5 - 10%

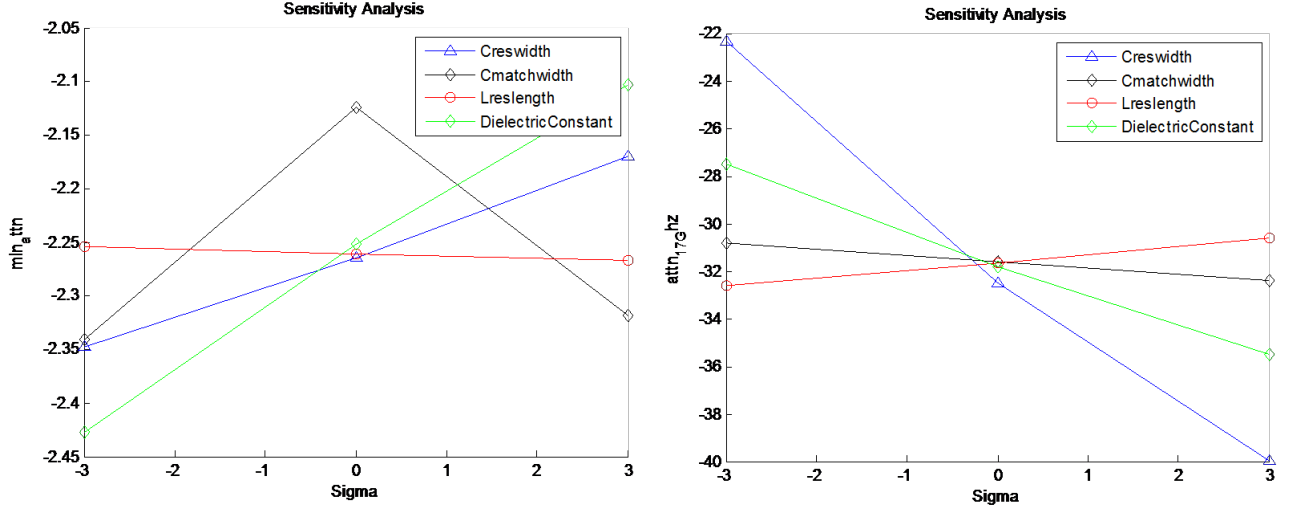
The performance specifications selected are the minimum attenuation and attenuation at 1.7GHz. The specifications for the performance measures are



**Figure 38:** Bandpass filter.



**Figure 39:** Typical variation of a performance metric ( $S_{21}$ ) for a bandpass filter.



**Figure 40:** Sensitivity plots for minimum attenuation and attenuation at 1.7Ghz.

$$\begin{aligned} min_{attn} &> -2.0db \\ attn_{17Ghz} &< -30.0db \end{aligned} \quad (27)$$

The sensitivity and curvefit plots, *pdfs* for the filter layout are as shown in Figures 40, 41 and 42.

Out of the measured 47 filters, only 6 of them satisfied the performance specifications in Equation 27. Hence the output yield value from the measurements is

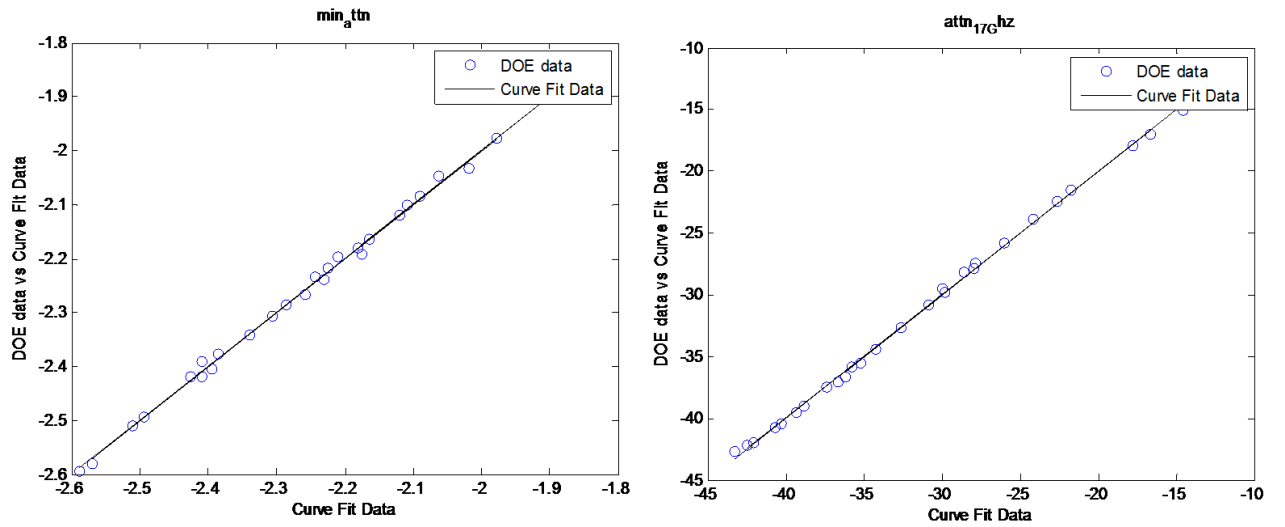
$$\frac{\text{Total number of filters satisfying the specifications}}{\text{Total number of filters measured}} * 100 = \frac{6}{47} * 100 = 12.76\% \quad (28)$$

In the table from the Figure 44, the output yield values from both the simulation and measurements can be seen. The yield values from both the cases agree. Thus, the methodology used for the statistical analysis is validated by the measurement data.

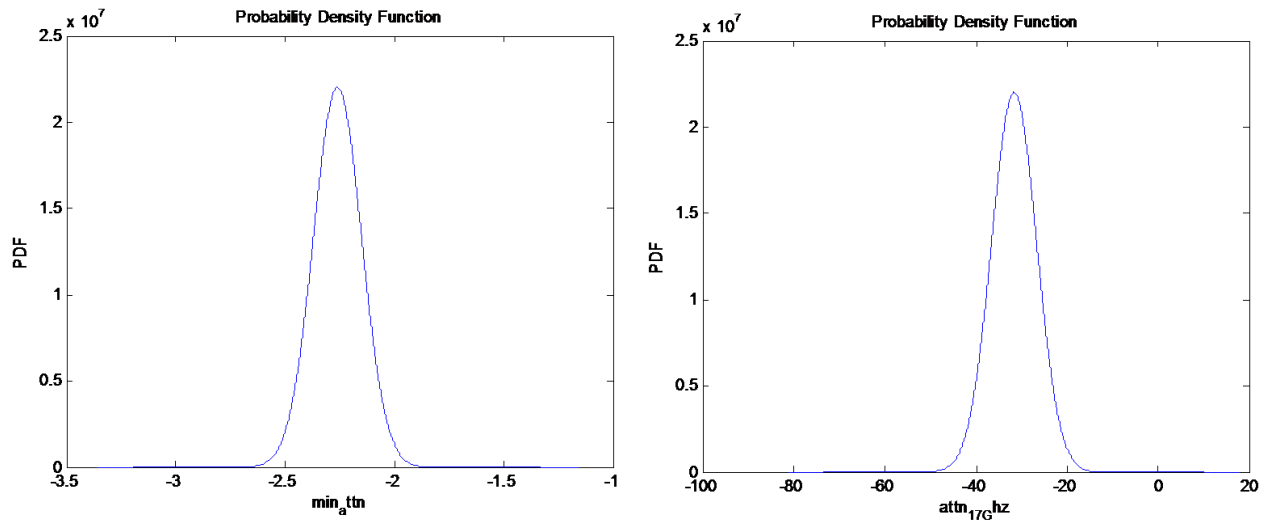
### 3.3 Test case 3 - Wirebonds

The test case consists of 2 wirebonds as shown in Figure 45.

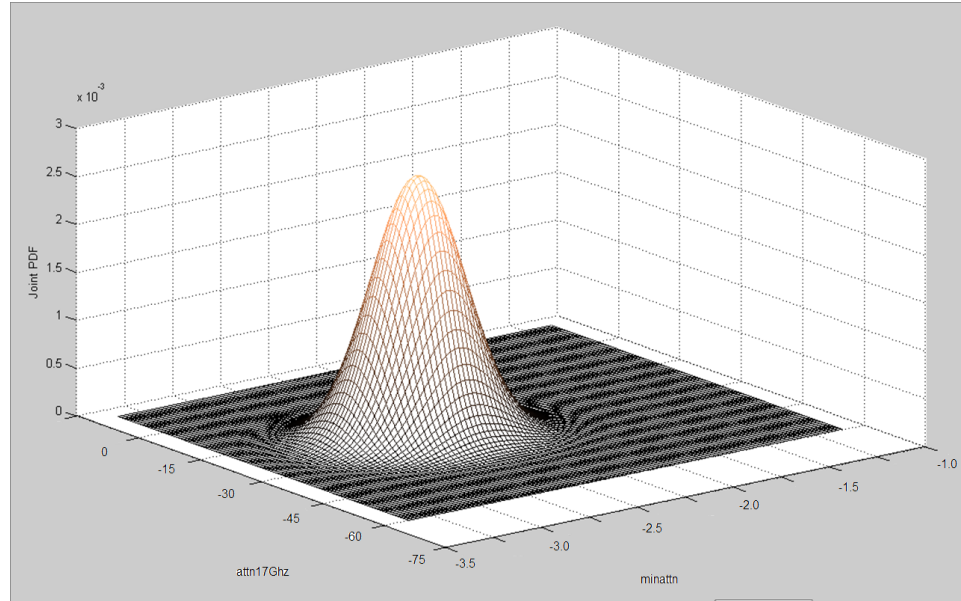
The simulation of the package layout is done using Mixed Signal Design Tools(MSDT-6) [13] [12].



**Figure 41:** Curvefit plot for minimum attenuation and attenuation at 1.7Ghz.



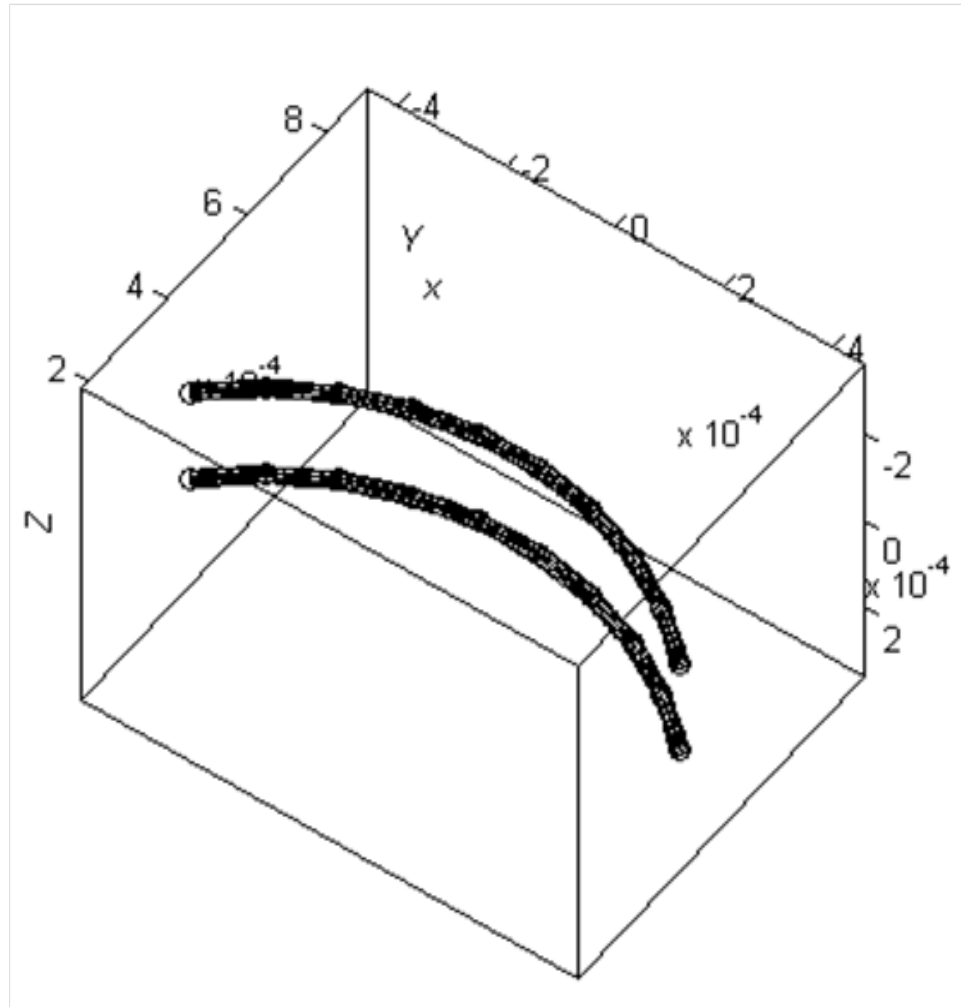
**Figure 42:** Pdf's for minimum attenuation and attenuation at 1.7Ghz.



**Figure 43:** Joint  $Pdf$  of minimum attenuation and attenuation at 1.7Ghz.

		From Simulations	From Measurements
Output Yield %		10.94%	12.76%
Minimum output yield%		10.937%	
Maximum output yield%		10.944%	
Line Width	51 mils	47.5 mils	
Dielectric Thickness 1	18 mils	18.25 mils	
Dielectric Thickness 2	36 mils	36.25 mils	

**Figure 44:** Comparison of output yield values from simulations and measurements. Nominal and design centered values of the input parameters from the simulations can be seen.



**Figure 45:** Wirebond structure



Three design parameters are selected for the test case. The design parameters chosen are the following:

1. Pitch between the two wires - *Pitch*
2. Length of the wires - *Length*
3. Angle of curvature - *Span*

Two performance measures are considered for this test case, resistance of the wire (in mohms), represented by  $R$  and loop inductance of the wires (in pH), represented by  $L$ . The performance specifications are as follows:

$$\begin{aligned} R &< 115\text{mohms}, \\ L &< 600\text{pH} \end{aligned} \tag{29}$$

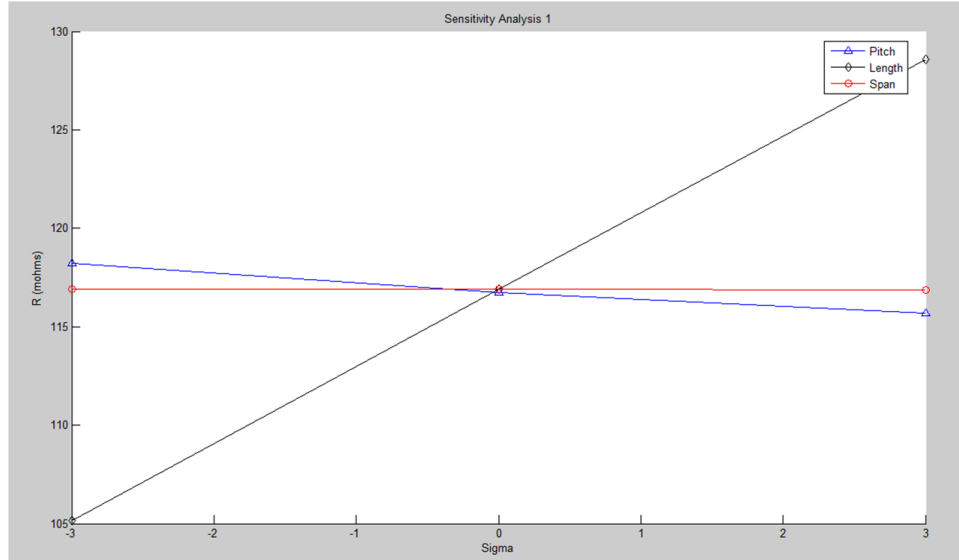
Full factorial plan is used to simulate this test case. The number of simulations done for full factorial plan is  $3^3 = 27$ . Figures 46 and 47 show the sensitivity plots of  $R$  and  $L$  respectively. Sensitivity analysis shows the variation of the performance measures when the design parameters are varied.

While creating the design of experiments (DOE's), the input parameters are varied at 3 levels. Let's suppose those levels as -3, 0 and 3. The Sigma on x-axis in the plots represents the 3 levels. Since all the design parameters are represented in the same plot, Sigma notation is used instead of using the original values of the design parameters.

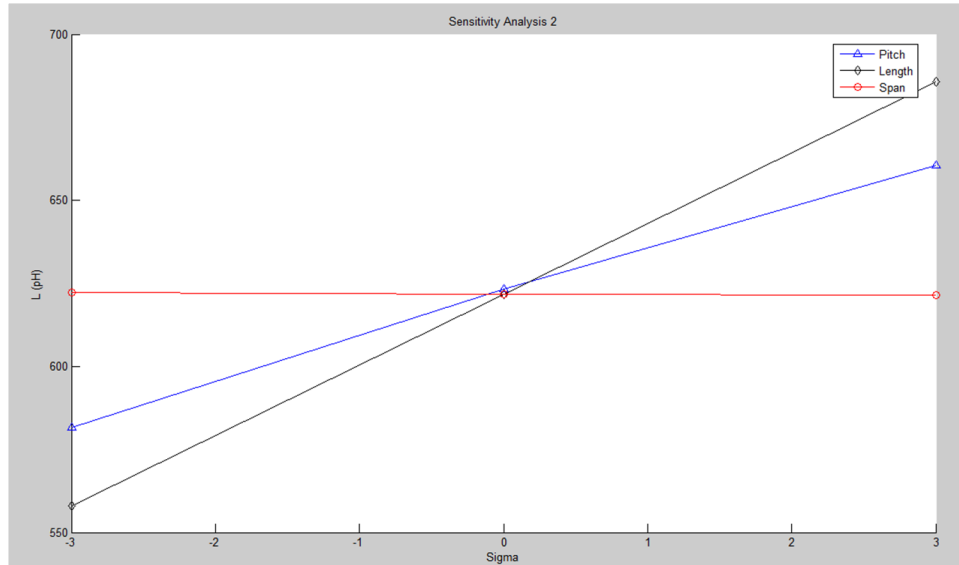
Figure 48 shows the response plot. The green curves in the plot represent the regression fit and 2 red curves show the boundaries of the regression fit by taking regression coefficient into account.

Figures 49 and 50 show the histograms of  $R$  and  $L$  respectively.

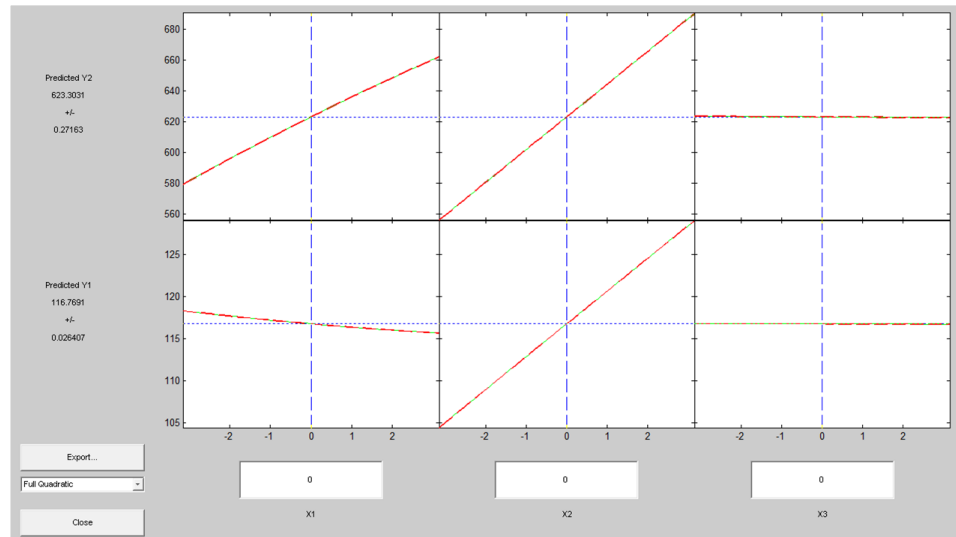
The PDF's of each of the performance measure show the Gaussian distribution of the convoluted experiments obtained from coefficients of the regression analysis.



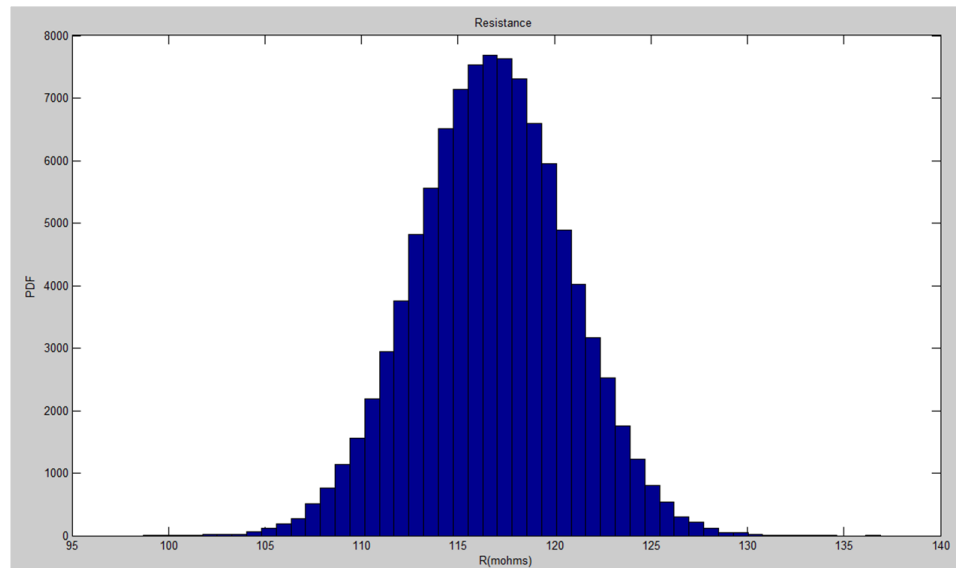
**Figure 46:** Sensitivity plot for resistance of the wire  $R$



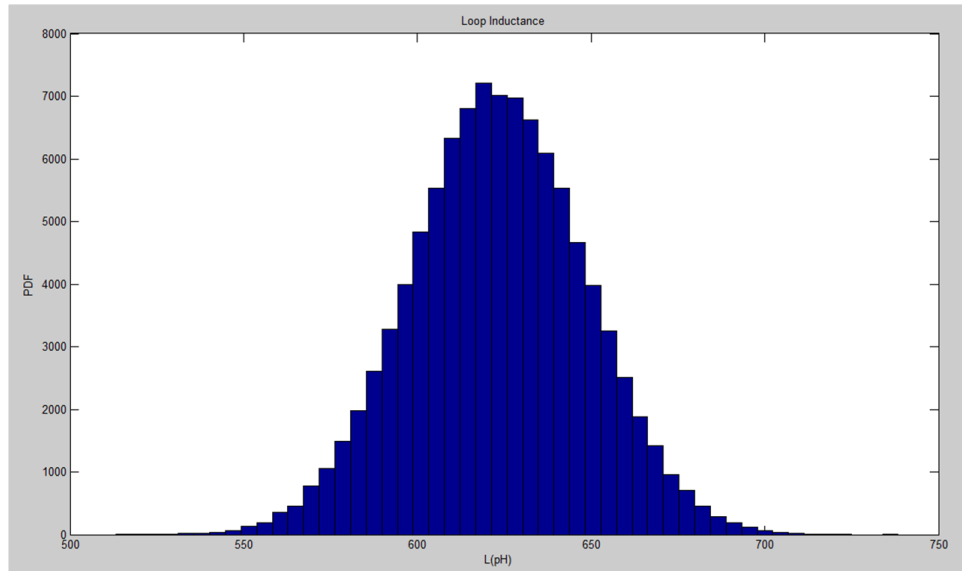
**Figure 47:** Sensitivity plot for loop inductance of the wires  $L$



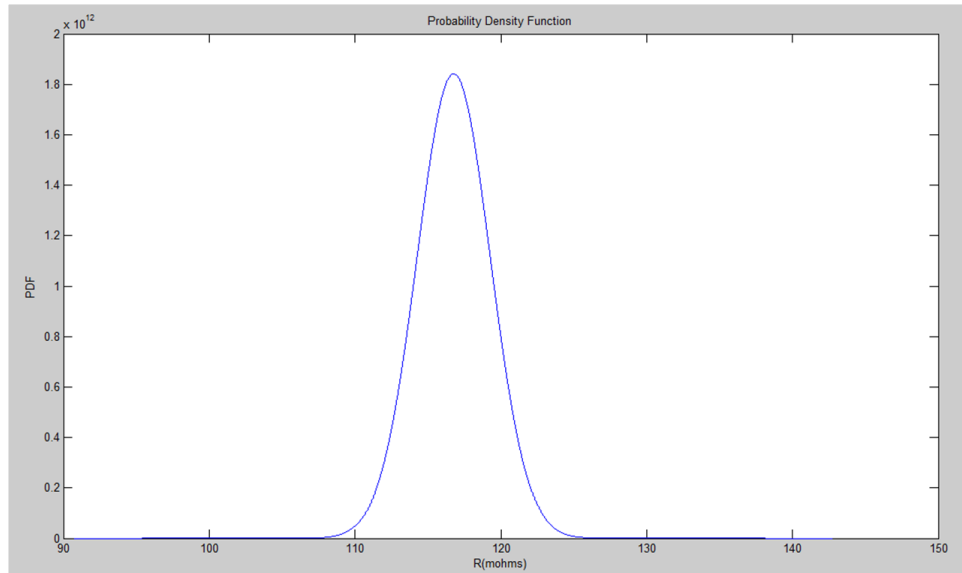
**Figure 48:** Response Plot



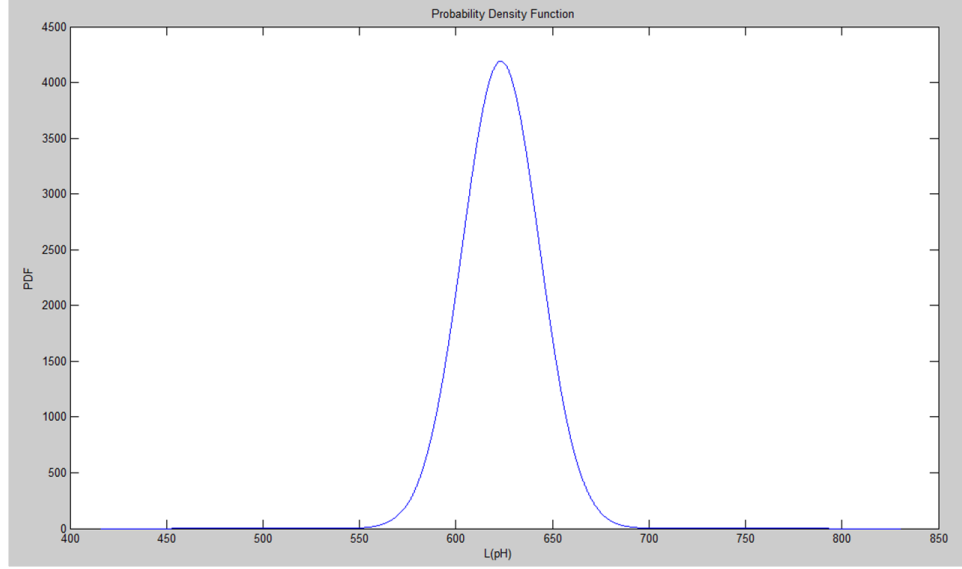
**Figure 49:** Histogram for insertion loss  $R$



**Figure 50:** Histogram for insertion loss  $L$



**Figure 51:** Probability density function plot for  $R$



**Figure 52:** Probability density function plot for  $L$

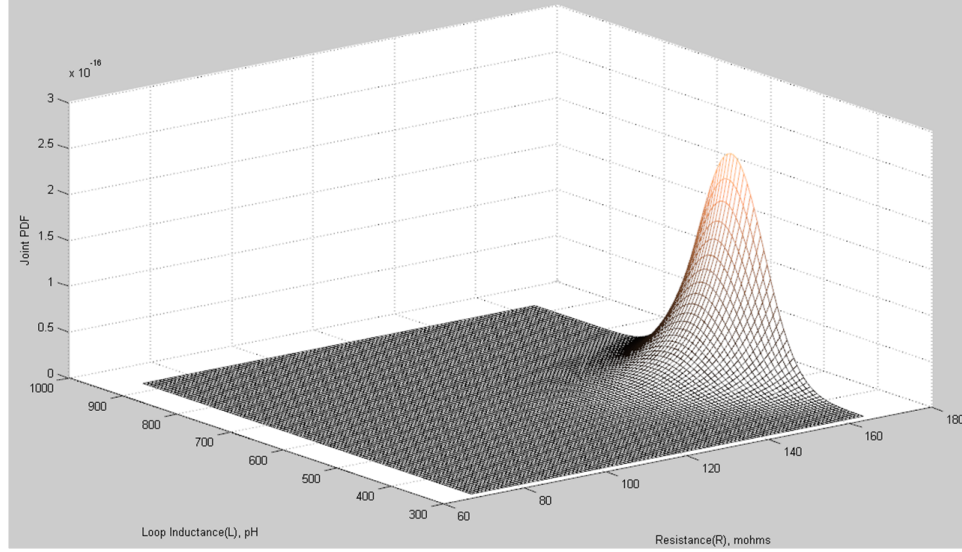
Figures 51 and 52 show the *pdf*'s of  $R$  and  $L$  respectively.

The Joint probability distribution function is the combined Gaussian distributions of all the PDF's of the performance measures. JPDF is used in calculating the output yield value. Figure 53 shows the Joint *pdf* of the performance measures.

The average parametric yield value obtained is 78.84%. Since there is no regression error, the boundary values of the output yield are also equal to the average value.

### 3.4 Summary

In this chapter, three test cases are presented. The first test case is a 4 layer package and the performance specifications look into the signal integrity of the package by choosing the insertion loss parameters as performance measures. The design of experiments are created in both full factorial plan and fractional factorial plan for 5 design parameters. Simulation is done and the results are presented. Both full factorial plan and fractional factorial plan give out similar results. Hence, the use of fractional facctorial plan is validated. Design centered values of the input parameters are given out.



**Figure 53:** Joint PDF

The second test case is an RF bandpass filter. Four input parameters are chosen and design of experiments are created. Statistical analysis is applied and the results are presented. A panel of filters are fabricated with process variations. They are measured and the output yield value is calculated with the same specifications as applied to the simulation part. The results are tabulated and the methodology is validated.

The third test case is DFM for wirebonds. Three input parameters are chosen and full factorial design of experiments are created. The results obtained by applying the statistical analysis are presented.

## CHAPTER IV

### CONCLUSION AND FUTURE WORK

#### *4.1 Conclusions*

In this dissertation, efficient statistical methodologies are presented for digital systems and embedded RF passive circuits. The proposed statistical diagnosis technique is based on layout segmentation, lumped element modeling, sensitivity analysis and extraction of probability density function using convolution methods. The statistical analysis takes into account the effect of the process variations that are incurred in batch fabrication. Yield enhancement and optimization methods based on joint probability distribution has also been presented. The results show good correlation with measurement and EM simulation data for embedded, RF bandpass filters fabricated in LCP-based substrate.

Design of experiment (DOE) principles are used to efficiently characterize the statistical disturbance space. This way, statistical distribution of the performance, and the most effective ways to reduce unwanted performance variations are obtained. Due to their efficiency in simulating large number of design parameters, Fractional factorial plan of DOE's are considered for the statistical analysis of large digital systems and embedded RF passive components.

The proposed statistical analysis and diagnosis methodology is unique in the way it addresses statistical variations for digital signal integrity and embedded RF passive circuit performance. The methodology has been successfully applied to large digital systems and embedded passive circuits. As a result, digital systems and embedded passive components can be manufactured with low cost processes at high yield. Consequently, cost effective digital and RF integration can be achieved.

In this dissertation, performance and yield figures of embedded passive circuits are analyzed during design phase. This information is used to improve design and optimize manufacturing technology. The methodology has been demonstrated on embedded RF bandpass filters fabricated using organic laminate technology. Parametric yield of the embedded filter design has been computed. In addition, design and manufacturing changes have been quantified for increasing the yield. This technique reveals the relation between design complexity, manufacturing variations, and yield.

As a result, high performance System-in-Packages (SiPs) can be fabricated using low cost technologies with greater flexibility.

Contributions of this research can be listed as follows:

1. Developed an efficient methodology for the statistical signal integrity analysis of large digital systems.
2. Demonstrated signal integrity analysis and verification process through design of experiment principles.
3. Developed a feasible alternative to conventional worst-case and Monte Carlo approach for signal integrity verification.
4. Developed and demonstrated efficient methodologies for the statistical analysis of embedded RF passive circuits and components.
5. Developed yield and performance improvement methods for embedded passive circuits for RF applications.

## ***4.2 Future Work***

In this study, variations of design parameters associated with separate manufacturing steps and system components were considered independent. To account for correlated design parameters, new analysis and diagnosis methods need to be developed. Experiment plans used in this study analyze the design parameters efficiently. To accommodate large number of design parameters, the size of the experiment plan



should be increased. To reduce the number of analyzed design parameters, principal component analysis (PCA) and common factor analysis (CFA) methods can be used. One of the major challenges in statistical modeling is obtaining the exact statistical distributions of design and manufacturing parameters. Studies can be conducted to collect more accurate distributions of such parameters. Then, the proposed statistical methodology can be adapted to these distributions.

Further improvements can be achieved by increasing the accuracy of electrical and statistical modeling. Advancements in the modeling and simulation of digital and RF systems will enable more accurate statistical analysis and diagnosis. Commercial simulation tools can be enhanced with statistical analysis methods to generate performance distributions.

In the statistical modeling, regression accuracy can be increased by using higher order sensitivity functions and nonlinear regression. Additional studies include non-Gaussian distribution of the design parameters to calculate the parametric yield.

## APPENDIX A

### MIXED SIGNAL DESIGN TOOLS (MSDT) - 2

#### Description of tool :

This tool applies fast and accurate layout-level statistical analysis methodology for System-in-Package (SiP) layouts. The approach is based on sensitivity analysis, regression analysis and extraction of probability density function using convolution methods. The statistical analyses were utilized as diagnosis tools to estimate distributed design parameter variations and yield of SiP layouts for given measured performances. Statistical methods were also applied for design space exploration to improve system performance by generating design centered values for the design parameters.

**Implementation** : Matlab

**Platform** : Windows (currently)

**Input Format** : Ascii Text File(.txt)

**Output Format** : Ascii Text Files(.doc); Automatic plotting in Matlab

**Release Date** : Version 1.0 - August 15, 2008

#### Tool Capabilities :

1. Integrated with MSDT (Mixed Signal Design Tools) - 1.
2. MSDT-2 supports DFM at package level layout. None of the commercial tools support DFM at the package level.
3. The conventional technique used for DFM is Monte Carlo analysis. However, Monte Carlo technique for EM simulations is time and memory intensive. The simulation time, in general, for a method of moments (MoM)-based iterative solver increases as  $O(n^2)$ , where  $n$  is the number of cells in the layout.

4. Design-of-Experiments method significantly reduces the number of EM simulations (by more than 50%) when compared to Monte Carlo method. Curve fitting and regression analysis techniques are used to obtain the missing data from DOE technique. Fractional factorial techniques can further reduce the number of EM simulations needed.

## APPENDIX B

### USER MANUAL/DOCUMENTATION FOR MIXED SIGNAL DESIGN TOOLS (MSDT) - 2

#### GETTING STARTED :

This section deals with the *Extracting, Installing, and Running MSDT-2*.

#### **Extracting and running the tool from the .ZIP archive**

##### Step 1:

Unzip the MSDT2\_Tool\_and\_Examples.zip file to a convenient location on the computer. WinZip or Winrar applications can be used to extract the contents to a desired location.

##### Step 2:

The folder MSDT2\_Tool\_and\_Examples should contain 2 subfolders

1. MSDT\_2 Tool
2. Test Cases

Check if the folders are present.

##### Step 3:

MSDT\_2 Tool folder contains the

1. MSDT\_2.exe - Executable file
2. MSDT\_2.prj - Project file
3. MSDT\_2.ctf - CTF file
4. MSDT\_2\_main.c - C File
5. MSDT\_2\_mcc\_component\_data.c - C File
6. mccExcludedFiles.log - Log File
7. MSDT\_2\_mcr - Windows Folder

## 8. readme.txt - Text File

All the files are required to run the MSDT-2 tool. The important files that the user must know about are the executable file and the text file.

MSDT-2 is run by double clicking the executable file. The text file is a 'read me' file which tells the user what to install to get the executable work. User must read the 'read me' file before running the executable to make sure he/she has all the required software.

Step 4:

'Test Cases' folder contains 3 test cases and a power point file showing the setup of the test cases. The first test case contains five different cases of the same layout example. It uses full factorial plan to get the Design of Experiments (DOE's). The second test case contains one example of the same layout as used in the first test case but it uses fractional factorial plan to get the DOE's. The third test case contains an example which used 10 design parameters and fractional factorial plan to get the DOE's. The MSDT2\_Test\_Cases\_setup.ppt file contains the setup of the test cases, the layout, design parameters and performance measures selected for each example, the plots and finally the comparison of full factorial and fractional factorial plans.

Step 5:

Once all the files are present on your computer, double click the executable file to select the example and run the MSDT-2 tool.

### **Input Interface**

A text file is used to provide input to the MSDT-2 Engine. The Text file should contain the following

1. [Type]

Accepted values - 1. It does not have any significance right now. Reserved for future use if more input interfaces are added.

2. [Design.Parameters]

This contains the names of the design parameters.

3. [Nominal\_values\_n.Tolerance]

It contains 2 columns. The first column corresponds to the nominal values of the design parameters. And the second column corresponds to the tolerance percentage. For example, if the nominal value is 5 and the tolerance percentage allowed is 10 then the first row looks like  $< 5 \ 10 >$ . The number of rows is equal to the number of design parameters.

4. [Performance\_Measures]

This contains the names of the performance specifications and the condition (either  $<$  or  $>$ ). The specification value is put in the next section. Right now, the number of performance specifications that can be entered are limited to 2.

5. [Performance\_specifications]

This section contains the performance specification value for the above mentioned performance measures.

6. [Design\_of\_Experiments]

This section contains the Design of Experiments, either full factorial or fractional factorial plans, and the performance specifications values. A delimiter '%' should be used after every section except at the end of the Design of Experiments.

### **Output Interface**

A series of plots and \*.dat files are created as part of Output Interface.

The plots that are shown are

1. Sensitivity Plots for each performance specification.
2. DOE data vs. Curve Fit data plots for each performance specification.
3. Response Surface plot where a user can see sensitivity plots. User can change the levels of design parameters and can see the corresponding change in the performance specifications.
4. Histograms for each performance specification.

5. Probability Distribution Functions for each performance specification.
6. Joint Probability distribution function.

The word files that are created have the following data

1. Sensitivity Plot data for each performance specification.
2. DOE data vs. Curve Fit data plot data for each performance specification.
3. Histogram data for each performance specification.
4. Joint probability distribution data.
5. Yield value with boundary values and Design centered values of the design parameters.

User can write a simple script to plot the graphs using the \*.dat files.

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